Journal of Air Transport Management 112 (2023) 102452

Contents lists available at ScienceDirect

Journal of Air Transport Management

journal homepage: www.elsevier.com/locate/jairtraman

Maximizing non-aeronautical revenues in airport terminals using gate assignment and passenger behaviour modelling

João Silva [a], Sofia Kalakou [b,*], Antonio R. Andrade [a]

[a] IDMEC, Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal

[b] Instituto Universitário de Lisboa (ISCTE-IUL) - Business Research Unit (BRU-IUL), Avenida das Forças Armadas, 1649 – 026, Lisboa, Portugal

ARTICLE INFO

Keywords:
Gate assignment problem (GAP)
Airport management
Mixed-integer linear programming (MILP)
Passenger behaviour
Airport revenue management

ABSTRACT

Airports must ensure that their operations can efficiently adapt to the emerging needs considering both the passenger experience and their economic viability. One way to achieve this is by optimizing the airport operations, aiming to maximize revenue levels considering operational objectives and passenger requirements inside the airport. This study presents an original mixed-integer linear programming model (MILP), which combines the gate assignment problem with passenger behaviour modelling. First, a survey was conducted to collect relevant information to model passenger behaviour and the purchases conducted in a terminal, leading to the estimation of discrete choice models that quantify the probability that a passenger makes purchases of certain levels at the terminal according to their flight type (departure, arrival or transfer). Then, the proposed MILP model assigns gates which would expectedly increase the airport non-aeronautical revenues at the terminal airport by matching flights and passenger gate categories to the most profitable gates, considering the proximity to the retail area, the walking distance needed to get to a gate in a specified time-horizon and the operational constraints of the airport. The application to the Lisbon Airport case study showed a potential increase of 8%–12.2% in revenues corresponding to 1732.7€ and 2967.3€ in half-an-hour time slots.

1. Introduction

Under a volatile aviation environment, airports are called to efficiently respond to the challenging management of passengers and aircraft operations ensuring both their economic viability and the improvement of passengers' experience. In this endeavour, the proper management of airport resources is of paramount importance. Airport gates are part of such resources and the allocation of flights to these gates is a daily challenge for airport managers. At the same time, as the non-aeronautical component of airport revenues holds a large share of total airport revenues, research opportunities arise to include non-aeronautical activities as a dimension in the planning of airside and landside airport operations. Not long ago, airports had to identify strategies to increase non-aeronautical revenues (Freathy 2004), and cope with several drivers of change in the airport management, through a series of strategic measures designed to generate commercial revenues, including the preservation and segmentation of the customer base (Freathy 2004). In fact, airports that diversified their revenue sources (including non-aeronautical revenues) have also become more efficient (Tovar and Martin-Cejas 2009). Currently, non-aeronautical revenues may even represent more than 50% of total airport revenue, and therefore, different research studies in enhancing passenger experience have been conducted (Fasone et al., 2016). In order to do so, a comprehensive understanding of passenger perceptions and behaviours inside airports and its relationship to airport infrastructure management is required.

According to Frank (2011), airport managers have put their efforts on non-aeronautical revenues from retailing activities. However, a paradox exists: efficiency requires minimizing waiting time prior to boarding so that parking charges decrease for airlines, whereas passenger spending more time in the airport fill their waiting time in retail and beverage. It is rather the retail business than landing fees and service charges that make airport operations viable (Vogel 2011), as larger passenger volumes create greater opportunities for terminal retail revenues (Appold and Kasarda 2006, 2011; Fuerst et al., 2011). Therefore, retailing activities and commercial partners are essential elements in value creation in airport business models (Rotondo 2019). In fact, their service attributes are some of the many airport attributes that influence the air traveller satisfaction (Fakfare et al., 2021).

Passengers and aircrafts are handled through airport operations and

* Corresponding author.
E-mail addresses: sofia.kalakou@iscte-iul.pt (S. Kalakou), antonio.ramos.andrade@tecnico.ulisboa.pt (A.R. Andrade).

https://doi.org/10.1016/j.jairtraman.2023.102452
Received 11 April 2022; Received in revised form 20 March 2023; Accepted 19 June 2023
Available online 9 July 2023
0969-6997/© 2023 Elsevier Ltd. All rights reserved.

are used as inputs and outputs of complex airport processes. The goal of this paper is to deliver a joint modelling approach of aircraft operations and passenger behaviour, leading towards an operational management framework that is cost-efficient and passenger centric. A modelling approach that combines simulation and optimization techniques for gate assignment is followed leading to the development of an original Mixed-Integer Linear Programming (MILP) model that includes the passenger behaviour dimension expressed as probabilities of purchasing levels (€) in the airport terminal.

A three-fold methodology is applied. First, the optimization model for gate assignment is formulated. Then, a passenger survey is designed for the collection of passenger spending-related information and it is employed for the development of discrete choice models that simulate passenger purchasing behaviour. By considering information on passenger characteristics, experience and their purchasing behaviour, different purchasing categories per passenger type (departing, arriving or transferring passengers) are created. At the last step, the estimated probabilities on these different passenger categories are incorporated in the optimization model, so that the gate assignment that optimizes revenues and walking distances is designated. In a nutshell, the model increases the total spending of passengers at the airport by matching flights and passenger spending category to gates, considering the proximity to the retail area and the walking distances needed to get to the gates, in a specified time-horizon, while complying with several operational constraints. Although the consideration of walking distances has been analysed in previous research in terms of time and monetary value of gates, to the best of authors' knowledge, the results of passenger behavioural analyses and revenue maximization has not yet been linked to gate assignment models. The modelling work to be carried out in this study is innovative also by jointly considering different passenger flows and experiences. Nowadays with the significant losses faced by airports due to the current and unexpected disruption incurred since the international emergency of coronavirus, and the economic impacts on transport infrastructure, the better understanding of passenger behaviour can be a key to the recovery process of airport businesses.

This paper is structured in six sections. First, the current section introduced the need to do more research on non-aeronautical revenue management and its links to passenger behaviour and gate assignment. Then, section 2 presents the background research that contributed to the development of the current work, and afterwards, the methodology and the developed models are explained in section 3. The application of the methodology to the Lisbon airport follows in section 4, and finally, the paper presents the results and the implications for airport managers in section 5. Conclusions are provided in Section 6.

2. Literature review

2.1. Gate assignment models

Past research has broadly analysed the topic of gate assignment with early studies focusing on the minimization of the walking distances covered by passengers in an airport building (Haghani and Chen, 1998). Recommendations for airport planning also suggest this metric for airport design (IATA, 2014). Minimizing walking distances allows passengers to have time for their favourite activities, while having more time for themselves, either to discover new activities available at the airport or to relax while waiting for the boarding. However, the passenger experience many times entails long walks, no seating and few activities. Entwistle (2007) found that 85% of passengers want easy access to shops from departure lounges and more than 60% plan to use airport shops and cafes. With the increase of international flights, the need to minimize the distance covered by transfer passengers from gate to gate arose in airport planning (IATA, 2014) and respective gate assignment optimization models focused on walking times (Kim et al., 2017; Benlic et al., 2017) and the probability of transfer passengers losing their flight (Benlic et al., 2017). In previous studies, various walking distances have been considered. Jiang et al. (2013) in their multi-objective gate assignment model considered three passenger walking distances: i) the arrival passenger distance, namely the distance from gate to baggage hall; ii) the departure passenger distance, i.e. the distance from security check to gate and iii) the transfer walking distance, i.e. the distance from gate to transit counter and then to the gate of the next flight. Consideration of walking distances affects not only costs but also passenger satisfaction (Kim et al., 2017).

Another approach to gate assignment optimization is the fulfilment of airport and/or airline requirements and preferences related to the utilization of airport infrastructure and the processes that take place in it. Some common objectives concern the minimization of ungated flights (Deng et al., 2017), the minimization of the number of flights attributed to remote gates, which require the transfer of passengers by bus (Dell' Orco et al., 2017), and the maximization of satisfaction of airline preferences (Benlic et al., 2017). Regarding processes in the airside, i.e. where the aircrafts move, common objectives of the optimization problems have been the minimization of towing movements (movement of aircrafts on ground between gates) (Benlic et al., 2017; Dijk et al., 2019) and their associated costs (Kumar and Bierlaire, 2014; Yu et al., 2016, 2017).

Another suggested cluster of optimization objectives is related to the robustness of the achieved solutions to incurred changes in flight plans, e.g. due to possible flight delays (Daş et al., 2020). Three types of objectives have been suggested: i) those related to the idle time of the aircraft between flights (Benlic et al., 2017; Deng et al., 2017; Kumar and Bierlaire, 2014), ii) those that cater for gate conflicts (Yu et al., 2016, 2017; Castaing et al., 2016) and iii) those that measure the deviation from a reference schedule (Nikulin and Drexl, 2010).

Optimized solutions to gate assignment problems may consider one or multiple objectives. Considering the complexity of airport operations, the use of single objective optimization problems has been considered inappropriate and the approach of aggregating multiple objectives in one function by using weights has been adopted by various studies (Daş et al., 2020).

Recent approaches (Benlic et al., 2017; Yu et al., 2016, 2017; Mokhtarimousavi et al., 2018) in gate assignment tend to be all passenger-, airport- and robustness-oriented. In these studies, passengers are treated as a unidimensional agent with the same characteristics in all types of airports and models. However, as airports link international destinations the requirements, the preferences and the overall behaviour of the passengers vary. For airports, this is especially important, considering that passenger movements do not only generate aircraft movements and related aeronautical revenues but are also sources of non-aeronautical revenues generated by passenger behaviour using retail, beverage and other areas in the free time before boarding and these aspects vary among origins and destinations.

2.2. Passenger behaviour modelling

The importance of non-aeronautical activities and revenues has risen significantly (Graham, 2018) and the engagement to these activities varies among passengers and airports (Castillo-Manzano et al., 2018). Passenger clusters with common purchasing characteristics have emerged (Chung et al., 2013) and two types of passenger shopping behaviours have been identified (pre-planned or impulsive) according to shopping perceptions and purchase levels (Lin and Chen, 2013; Lu, 2014).

In the context of discretionary activities and non-aeronautical revenues, passenger-centric information has also been included in the modelling of passenger behaviour. Puls and Lentz (2018) conducted semi-structured interviews with executives and senior managers from Zurich and Basel airports, to explore the passenger shopping experience, and found out that personalized offerings can improve non-aeronautical revenues. However, such a passenger-centric concept can only be accomplished with richer data and indicators to identify the type of customer (e.g. impulsive buyer, mood shopper, shopping lover, etc.). Freitas et al. (2021) also discussed the role of the customer experience in a case study of the main Brazilian airports, finding out that passenger satisfaction levels were influenced by the passenger's profile and individual perception on commercial facilities and on food services. For instance, they showed that frequent flyers were less satisfied and passengers travelling alone were more satisfied. More recently, Pant (2022) also discussed the role of technologies in the behaviour of young adult travellers at airports, defending that improving insight on the social practices of young adult travellers and their use of self-service technologies at airports can increase non-aeronautical revenues even further.

Regarding the airport design and passenger behaviour, higher purchase levels have been associated to the closeness of the passenger's flight gate to the retail area (Geuens et al., 2004). Previous work has shown that walking distances are important to passenger activities, as they prefer to first walk until gate and then, according to the closeness and time availability, decide if they will go back to the retail area for shopping activities or not (Kalakou and Moura, 2015). As walking distances are dependent on gate assignment, the latter is a process that could influence the range of non-aeronautical revenues of an airport.

In general, the passenger experience can increase the passenger willingness to pay for more products and services (Crawford and Melewar, 2006). Passengers who arrive early at the airport and have time available before flight departure are more likely to spend money on food and drinks (Castillo-Manzano et al., 2011; Tseng and Wu, 2019) and use both commercial areas and services (Torres et al., 2005). The area of non-aeronautical activities also varies according to passenger characteristics (Kalakou and Moura, 2021). Passengers choose to spend more time in activities before the security checkpoint, especially when they travel in groups (Cheng et al., 2014), unless they have conducted the check-in online (Kalakou and Moura, 2015). Lower engagement to activities is expressed by passengers travelling with low-cost carriers (Castillo-Manzano et al., 2011) or with only carry-on baggage (Liu et al., 2014). Personal aspects of the passengers such as higher education, older age, higher income, female gender, travelling by aircraft with low frequency affect positively purchases in the airport (Castillo-Manzano, 2010; Liu et al., 2014; Del Chiappa et al., 2021). The group size may have various effects according to the group size; travelling with more people positively affects the purchasing behaviour (Castillo-Manzano et al., 2011) but when travelling in a group with children, this may impede the purchasing behaviour (Castillo-Manzano, 2010; Castillo-Manzano et al., 2011; Liu et al., 2014). The flight status may also affect passenger behaviour as delays may encourage engagement to retail activities (Wen et al., 2019; Choi and Park, 2022) but only up to a certain delay duration (Choi and Park, 2022).

2.3. Opportunities in mixed modelling approaches

Mixed approaches in gate assignment problems have led to the assignment of more passengers to gates that could increase shopping revenues through the minimization of walking distances and the maximization of the number of flights at gates close to the shopping area (Daş, 2017; Dijk et al., 2019). Dijk et al. (2019) considered an objective metric that aimed to maximize the potential revenue per gate and flight using data on purchases of specific flights per store derived from historical non-aeronautical revenue data of an airport and the number of stores between each gate and the retail area.

In current studies, the distances of the gates from retail areas have been monetized and associated in an aggregated way to non-aeronautical revenues generated by passengers. The disaggregated behaviour of passengers is still not explored. This constitutes a gap in the state-of-the-art and an opportunity to develop behavioural models that could enrich the current gate assignment optimization models. The contribution of integrating such passenger simulation models has been previously illustrated in Kalakou et al. (2015) and Wu and Chen (2019). Passenger purchasing behaviour could be integrated in the gate assignment process so that optimum allocations of flights to gates are decided leading to revenue maximization while complying with operational and business objectives. Such a process could be of great utility to airport managers who could have the opportunity to make decisions on their gate assignment plans by maximizing the efficiency in the utilization of their gates and the generation of non-aeronautical revenues.

Airport operators are called upon to efficiently handle both aircraft and passenger movements, satisfying the needs of airlines and passengers. Serving high volumes of passengers and aircrafts demands efficient airport operations that will ensure a pleasant passenger experience in the terminal and smooth aircraft movements between the terminal, the apron area and the runway. The airport gates mark the border line of the landside and the airside of an airport. At this point aircrafts disembark arriving passengers to embark departing passengers. This transition marks the beginning or the end of the passenger experience in the terminal and is the intermediate point of the aircraft's journey in the airport; after reaching a gate an aircraft needs either to get prepared for a new flight departure or park in the airport stands until the next departure.

At the planning stage of an airport, the airport design provides the appropriate conditions for the safe and smooth movement of aircrafts in the airside area. At the operational stage of an airport, airport management decisions determine the efficient operation of this area. An important task at this stage that controls the movements of aircrafts is the process of gate assignment of flights to gates. Gate assignment is a challenging task considering the uncertainties related to aircraft arrival and departure times and the adjustments required during a day due to delays and/or cancelations. For example, in 2018 the share of flights in European airports "arriving within 15 min of their scheduled time was 75.7% and the average departure delay was 14.4 min in 2018" (Eurocontrol, 2018). Such deviations from the flight plans cause delay propagations among airports and require airport managers to adjust very often their gate assignment plans during a day so that they manage to accommodate all flight arrivals and departures by matching airlines' demand in gates and parking stands with the airport's supply, namely its capacity.

The current work looks at the gate assignment task of airport operators in a holistic view of airport management encompassing operational aspects of optimizing the flight allocation to airport gates and better managing passenger flows. Passengers care for many more aspects during their stay at the airport than walking distances, which has been the principle aspect considered in the literature. Considering the complexity of the human nature and decision-making, it is suggested that additional aspects can be included in mathematical formulation of the gate assignment problem catering for more passenger-centric dimensions of the problem.

3. Methodology

The gate assignment problem is a challenge for airports and airline companies as it entails a large number of flights and schedules and how it affects the passenger experience. Airports are called to allocate flights to gates in the most efficient way, corresponding to the airlines' requests for a gate and ideally increasing passenger consumption in the airport terminal. This allocation process has to comply with certain operational constraints, e.g. a departing flight to a non-Schengen destination can only be assigned to a gate that has a passport control infrastructure. Moreover, a flight can only be assigned to a gate capable of receiving a flight of such conditions, e.g. an Airbus A300 cannot be assigned to a gate that is only able to operate smaller aircrafts due to structural and/or operational restrictions. Therefore, flights and gates are classified so that these compatibilities in the allocation process can be constrained. Passenger consumption is also defined using different purchasing levels and the different passenger categories (departing, arriving and transfer passengers). Therefore, different classes of passengers can be defined to distinguish their different categories and purchasing power level (please see Table 2 of Section 4 for an example).

Consequently, an optimization model is presented in this study to combine all the associated variables and obtain an optimized gate allocation. The formulation intends to take the perspective of the airport manager, who aims to both satisfy airline and passenger requirements and ensure the economic viability of non-aeronautical activities, specifically the ones related to retail. Thus, it is aimed to minimize the walking distance that a passenger needs to walk to arrive at the gate, while maximizing the potential revenues arising from passenger purchases. In this process, airport restrictions and airline requirements are also considered. Three different passenger types are used in this formulation: arriving, departing and transferring passengers. Later, by using the survey data, an assignment is made to the probability of spending a certain amount of money per each passenger category and passenger type (arriving, departing and transferring). In practical terms, the optimization process will allow that the passengers with higher probability of spending money to be the closest as possible to the centre of retail area.

The present mathematical model is based on the model developed in Lim et al. (2005) which allows a time window for each flight, so that the actual arriving and departure times do not have to be fixed to a certain schedule. Instead, they are able to slide in the flight "time-window". Some variables and constraints were used based on 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 some other constraints. The proposed model is a Mixed-Integer Linear Programming, which was implemented in the optimization software FICO Xpress (version 8.11) and run in a 16 GB (RAM) computer with an Intel Core i7-7700k processor (4.20 GHz).

Fig. 1 provides a simple representation of the sequence of times associated to a given flight j. Prior to gate assignment, there is an expected time window $[a_j, d_j]$, i.e. between the expected arrival time and the expected departure time, in which a gate assignment decision is made and arriving passengers may disembark the aircraft at time b_j and departing passengers may embark the aircraft at time c_j.

The original model is presented below, detailing the constants and sets (section 3.1), the parameters (sections 3.2), the decision variables (section 3.3), the objective function (section 3.4) and finally the constraints (section 3.5).

3.1. Constants and sets

N_G Number of gates
N_F Number of flights
N_{PC} Number of passenger categories
$\boldsymbol{G}$ Set of gates $\boldsymbol{G} = \{1, \ldots, N_G\}$
$\boldsymbol{F}$ Set of flights $\boldsymbol{F} = \{1, \ldots, N_F\}$
$\boldsymbol{P}$ Set of passenger categories $\boldsymbol{P} = \{1, \ldots, N_{PC}\}$

3.2. Parameters

a_j	The expected arrival time (in minutes) of flight j
d_j	The expected departure time (in minutes) of flight j
$n^a_{p,j}$	Number of passengers arriving at the airport from flight j, according to passenger category p
$n^d_{p,j}$	Number of passengers departing on flight j, according to passenger category p
n^t_{p,j,j_2}	Number of passengers in transfer from flight j to flight j_2, according to passenger category p
w^a_i	Walking distance of arriving passengers from gate i to the baggage claim area
w^d_i	Walking distance of departing passengers from the main retail area to gate i
w^t_{i,i_2}	Walking distance between gate i and gate i_2
$r^a_{p,i}$	Revenues from arriving passengers of category p $^{\text{arriving at gate}}$ i
$r^d_{p,i}$	Revenues from departing passengers of category p, departing from gate i
$r^t_{p,i}$	Revenues from transfer passengers of category p, arriving at gate i
c^a_p	Cost per distance of arriving passengers of category p
c^d_p	Cost per distance of departing passengers of category p
c^t_p	Cost per distance of transferring passengers of category p
g_i	Classification of gate i
g^S_i	Classification of gate i if Schengen or non-Schengen
f_j	Classification of flight j
f^S_j	Classification of flight j if Schengen or non-Schengen
θ_i	Time (in minutes) from runaway to gate i and vice versa
δ_i	Prepare time for departure or arrival between pilot and airport manager and time required for passengers to enter/leave the aircraft from/to gate i (in minutes)
τ^t_{i,i_2}	Minimum time (in minutes) to allow transfer between gate i and gate i_2
τ_i	Minimum time (in minutes) of free-gate between two flights in gate i
$x^P_{i,j}M$	Gate allocation of flight j at gate i staying on the ground before the time interval studied Large number (e.g. $M = 10^5$)

3.3. Decision variables

Three binary decision variables are defined:

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

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

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

Two additional decision variables are defined, which are linearly dependent on decision variable $x_{i,j}$ through equations (12) and (13).

b_j Time that passengers disembark flight j. Note that, in the optimization model in constraint (12), the variable b_j is a linear dependent variable of $x_{i,j}$

c_j Time that passengers board flight j. Note that, in the optimization model in constraint (13), the variable c_j is a linear dependent variable of $x_{i,j}$.

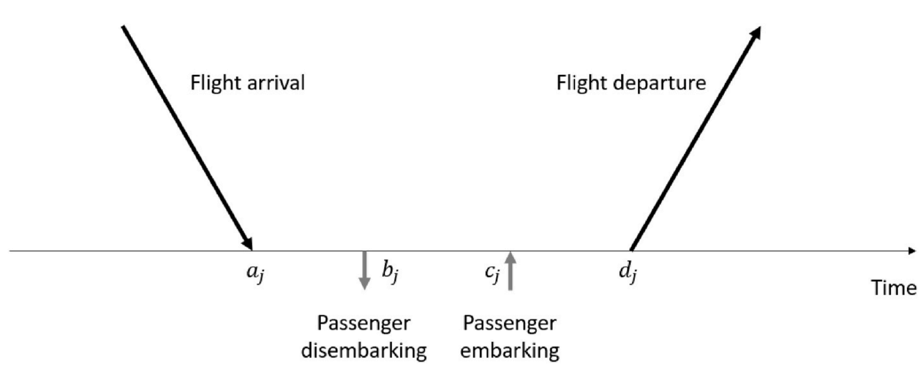

Fig. 1. Sequence of times for flight j: expected arrival time (a_j), time that passengers disembark the aircraft (b_j), time that passengers embark the aircraft (c_j) and expected departure time (d_j).

3.4. Objective function

The objective function (1) consists of six components (O_1, O_2, O_3, O_4, O_5 and O_6), detailed respectively in Equations (2)–(7). The first three components quantify the money spent by passengers: O_1 corresponding to revenues from transferring passengers, O_2 from arriving passengers and O_3 from departing passengers. The last three components correspond to the minimization of costs associated with walking distances for transferring passengers (O_4), for arriving passengers (O_5) and departing passengers (O_6).

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

With each component of the objective function defined as:

$$O_1 = \sum_{i=1}^{N_G} \sum_{i_2=1}^{N_G} \sum_{j=1}^{N_F} \sum_{j_2=1}^{N_F} \sum_{p=1}^{N_{PC}} n^t_{p,j,j_2} \cdot r^t_{p,i} \cdot z_{i,i_2,j,j_2} \tag{2}$$

$$O_2 = \sum_{i=1}^{N_G} \sum_{j=1}^{N_F} \sum_{p=1}^{N_{PC}} n^a_{p,j} \cdot r^a_{p,i} \cdot x_{i,j} \tag{3}$$

$$O_3 = \sum_{i=1}^{N_G} \sum_{j=1}^{N_F} \sum_{p=1}^{N_{PC}} n^d_{p,j} \cdot r^d_{p,i} \cdot x_{i,j} \tag{4}$$

$$O_4 = \sum_{i=1}^{N_G} \sum_{i_2=1}^{N_G} \sum_{j=1}^{N_F} \sum_{j_2=1}^{N_F} \sum_{p=1}^{N_{PC}} n^t_{p,j,j_2} \cdot c^t_p \cdot w^t_{i,i_2} \cdot z_{i,i_2,j,j_2} \tag{5}$$

$$O_5 = \sum_{i=1}^{N_G} \sum_{j=1}^{N_F} \sum_{p=1}^{N_{PC}} n^a_{p,j} \cdot c^a_p \cdot w^a_i \cdot x_{i,j} \tag{6}$$

$$O_6 = \sum_{i=1}^{N_G} \sum_{j=1}^{N_F} \sum_{p=1}^{N_{PC}} n^d_{p,j} \cdot c^d_p \cdot w^d_i \cdot x_{i,j} \tag{7}$$

3.5. Constraints

The objective function (1) is subject to the following constraints:

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

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

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

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

$$b_j = a_j + \sum_{i=1}^{N_G} (\theta_i + \delta_i) \cdot x_{i,j} \qquad \forall j \in F \tag{12}$$

$$c_j = d_j - \sum_{i=1}^{N_G} (\theta_i + \delta_i) \cdot x_{i,j} \qquad \forall j \in F \tag{13}$$

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

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

$$y_{j,j_2} + y_{j_2,j} \ge z_{i,i,j,j_2} \qquad \forall j, j_2 \in F, i \in G \wedge j \ne j_2 \tag{16}$$

$$g_i \ge f_j \cdot x_{i,j} \qquad \forall j \in F, i \in G \tag{17}$$

$$x_{i,j} = 0 \qquad \forall j \in F, i \in G \wedge g^S_i \ne f^S_j \tag{18}$$

$$c_{j_2} - b_j \ge \tau^t_{i,i_2} \cdot z_{i,i_2,j,j_2} \qquad \forall j, j_2 \in F;\ i, i_2 \in G \wedge \sum_{p=1}^{N_{PC}} n^t_{p,j,j_2} \ge 0 \tag{19}$$

$$b_{j_2} - \delta_i - \tau_i - c_j - \delta_i \ge -M.\left(2 - x_{i,j} - x_{i,j_2}\right)$$
$$\forall j, j_2 \in F;\ i \in G \wedge j \ne j_2 \wedge a_j \le a_{j_2} \tag{20}$$

$$x_{i,j} \le x^P_{i,j} \qquad \forall j \in F, i \in G \tag{21}$$

$$x_{i,j} \in \{0, 1\} \qquad \forall j \in F, i \in G \tag{22}$$

$$y_{j,j_2} \in \{0, 1\} \qquad \forall j, j_2 \in F \tag{23}$$

$$z_{i,i_2,j,j_2} \in \{0, 1\} \qquad \forall j, j_2 \in F;\ i, i_2 \in G \tag{24}$$

Constraints (8)–(16) are similar to the ones introduced by Lim et al. (2005). Constraint (8) ensures that each flight is assigned only to a single gate. Constraint (9)–(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 when the aircraft is ready to disembark passengers the following time sequence is taken into consideration: the moment the aircraft touches land (a_j), the time from the runway to the gate (θ_i) and the time needed for the aircraft to inform the tower of their arrival to the gate and other bureaucratic and security reasons (δ_i). In the same way, constraint (13) ensures that in the moment the aircraft is expected to leave the ground (d_j), it is necessary to consider the time needed for the aircraft to communicate their readiness to leave the gate to the tower and other bureaucratic and security reasons (δ_i), as well as the time needed for the aircraft to go from the gate to the runway (θ_i). Note that constraint (8) ensures that, for a given flight j, a single gate is assigned, and thus a single addition/reduction of time ($\theta_i + \delta_i$) are considered in constraint (12)/(13). This assumes that a flight has additional times that are the same for the landing to gate and for gate to departure. Moreover, it is also assumed that these additional times ($\theta_i + \delta_i$) are known in advance and do not change due to congestion or other delay event. In fact, these additional times can be simplified to $\delta_i = \delta = 3$ min, for instance.

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) was adapted from Lim et al. (2005) and specifies that one gate cannot be occupied by two flights simultaneously.

Constraint (17) ensures that a flight can only be assigned to a gate capable of receiving a flight of such conditions. For example, an Airbus A300 cannot be assigned to a gate that is only able to operate smaller aircrafts due to structural and/or operational restrictions. However, a smaller aircraft can be assigned to a gate with a higher capacity to receive a larger aircraft.

Constraint (18) ensures that an arriving (or departing) flight from (or to) a Schengen origin (or destination) is assigned to a corresponding gate that has the infrastructure needed (e.g. passport control). Moreover, a non-Schengen flight cannot be assigned to a Schengen gate.

Constraint (19) ensures that for a transfer to occur, there needs to be a minimum time between flights occupying 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 aircraft needs to be taken into account.

Constraint (20) ensures that each gate can only take one flight at a time. First, note that we are assuming that if flight j lands first than flight j_2 (note that the constraint is only valid for $\forall j, j_2 \in F$:; $a_j \le a_{j_2}$), then it will be assigned to a gate first. Moreover, flights cannot occupy the same gate within the same time window. Therefore, if any binary decision variable $x_{i,j}$ or x_{i,j_2} is equal to 1, then constraint (20) will not impose anything between disembarking time b_{j_2} and embarking time c_j. However, if both binary decision variables $x_{i,j}$ and x_{i,j_2} are equal to one, then b_{j_2} (the disembarking of passengers from flight j_2) can only happen after c_j plus $2\delta_i + \tau_i$ (embarking of passengers from flight j plus two prepare times for departure or arrival ($2\delta_i$) and the minimum time of free-gate between two flights in gate i (τ_i). Note that constraints (12) and (13) support the computation of b_{j_2} and c_j, respectively.

Constraint (21) allows the user to enter the flights that are already on the ground before the gate assignment, i.e. it constrains the gates that are already occupied and thus, it does not allow the model to use the same gate for another flight. To introduce this in the model, a parameter is added $x^P_{i,j}$, which is equal to 1 when gate i and flight j are already assigned previously to the desired time horizon to be optimized, and 0 otherwise. Finally, constraints (22), (23) and (24) specify that the decision variables $x_{i,j}$, y_{j,j_2} and z_{i,i_2,j,j_2} are binary variables.

4. Modelling passenger behaviour

A survey was designed and conducted through a web-based revealed preference survey to airport travellers, who experienced departing, arriving or transferring at Terminal 1 of Lisbon Airport. Terminal 2 was excluded from the survey. The survey was designed using 'Google Forms' application and allowed to divide the respondents in three different groups: departing, arriving or transferring passengers. The purpose of the survey was to gather useful information on how passengers behave inside the airport in order to develop discrete choice models to estimate the passengers' purchasing power, which can later be integrated in the gate assignment optimization model presented in section 3. Information on time-related aspects, passenger personal characteristics, the air trip features, the activities and purchases performed by the passenger while at the terminal and the easiness of orientation of the passenger inside the airport were collected. Passengers were categorized into groups according to their purchasing levels and the use of the airport (arrival, departure, transfer). The probability of belonging to each group was modelled using discrete choice modelling and included in the optimization model through the estimation of the number of passengers for each passenger type: arriving (n^a), departing (n^d) and transferring (n^t) passengers.

4.1. Survey and descriptive statistics

Lisbon Airport, also known as Humberto Delgado Airport or Portela Airport, is the largest and most important airport in Portugal. It has 2 civil terminals (T1 and T2) and one military terminal. The airport is the main hub to the Portuguese front-carrier TAP Air Portugal and is run by ANA Aeroportos de Portugal, VINCI Airports, S.A, which in combination with Portway - Handling de Portugal, S.A, comprise the ANA Group. The growth levels achieved in Portugal have been high due to the low-cost carriers consolidating their market presence and development of touristic offer in Portugal. The numbers show the significant development of air traffic throughout the years. According to ANA (2018), in 2018, there were 214,187 aircraft movements (plus 4.6% than in 2017) and 29.284 million passengers (plus 6.5% than in 2017), which accounts 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, which corresponds to 611.5 M€. In terms of non-aviation business, it represented 26.3% of the total turnover of the ANA Group, corresponding to 218.7 M€, with the retail business representing 56.4% of the non-aviation income. In this section, the application results to Lisbon airport are presented and discussed.

To obtain data on passenger characteristics, a survey was conducted to passengers that have departed, arrived or had a transfer at Terminal 1 of Lisbon Airport. Aspects related to time management, personal information, air-trip information, the activities performed in the terminal and orientation information were collected. The gathered data can provide insights on passenger choices, which are of potential interest to airport managers in order to complement their decision-making process on gate assignment, with this additional knowledge on passenger behaviour.

In total, 650 individuals fully completed the survey, with 447 answers corresponding to departure trips, 609 to arrivals at Lisbon Airport and 349 answers about a transfer done at any airport in the world. This was added to the survey, since it was almost impossible to guarantee a satisfactory number of answers from passengers transferring at Lisbon Airport. The survey was also separated in terms of type of passenger and each one will be shortly described. Some descriptive statistics from the sample are presented in Table 1.

4.2. Modelling passenger purchasing behaviour

Passenger purchases were modelled in categories according to their purchasing levels. For the departure passengers, four alternatives were considered: i) no purchases, ii) purchases lower than 8€, iii) purchases that ranges between 8 and 30€, and finally iv) purchases of more than 30€. 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). The value of 30€ represents an average purchase of the sample. For the arriving passengers, two alternatives were considered: no purchases or purchases. This separation was chosen since there were a lot of answers with 0€ spent at the airport. Finally, for transfer passengers, three alternatives were defined: i) spending nothing, ii) spending between 0 and 32€ or iii) spending more than 32€. The value of 32€ represents the average purchase of transfer passengers. Table 2 summarizes the proposed purchasing levels for the different passenger categories, and the associated average revenue per passenger (Table 2).

Next subsections 4.2.1 to 4.2.3 present the estimated discrete choice models for each purchasing level defined in Table 2, with the associated equations, their explaining variables and associated estimated parameters, and some goodness-of-fit statistics, for the three passenger categories: departing, arriving and transfer passengers. All the models' quality was addressed by the differences observed in the log-likelihood values every time a new variable was considered and the changes in the adjusted ρ^2 values. For the estimation of the models was used part of the sample (80%) while the rest was employed to validate the results. Biogeme software was used for the estimation of the models (Bierlaire, 2003).

4.2.1. Departing passengers

It was proved that socioeconomic and air-trip related variables had an impact on passenger choices. The variables that are expected to affect the utility of each alternative appear in its formulation and their explanation has a comparative character to the other alternatives.

Regarding the impact of the age of the passenger, our results demonstrate that very young travellers (18–22 years old) are more likely to make no or few purchases compared to medium and high as the positive values of the parameters reveal ($\beta_{age18\_22\_none}$, $\beta_{age18\_22\_few}$, $\beta_{age18\_22\_medium}$). This result is partially aligned with past literature; Liu et al. (2014) concluded that young passengers make purchases while our results also show there is high probability of not having purchases as well. Older passengers are more likely to make high purchases as the sign of the relevant parameters shows ($\beta_{age30\_50\_none}$, $\beta_{age30\_50\_few}$, $\beta_{age30\_50\_medium}$). In past research it was also found that as age increases, passengers tend to spend less often but when they do spend their purchases are higher (Lehto, Cai, O'Leary and Huan, 2004).

For the income of the passengers, we saw that there is a higher probability of having medium, few or no purchases compared to high ($\beta_{incomeComfort}$). Actually, high purchases were not favoured by high income as the positive signs of income variables demonstrate for the utilities of none, few and medium.

Passengers who arrive at the airport by car or personalized paid

Table 1
Socioeconomic statistics of the sample.

Variable	Category	% of total sample
Gender	Male	53%
	Female	47%
Age	18_22	21%
	22_29	27%
	30_50	38%
	51_65	12%
	More than 65	2%
Nationality	Portuguese	94%
	Other European	4%
	Not European	2%
Income status	Loose	22%
	No difficulty to live	68%
	Some difficulties to live	5%
	No income	5%
Departure time	Morning	40%
	Afternoon	39%
	Night	21%
Arrival mode	Car	17%
	Car lift	32%
	Ride hailing	19%
	Metro	11%
	Taxi	10%
	Bus	2%
	Other (hotel bus, train)	9%
Air trip purpose	Business	22%
	Studies	13%
	Holidays	49%
	Personal	16%
Air trip frequency	No air trip/year	2%
	1-3 air trips/year	50%
	4-12 air trips/year	40%
	More than 12 air trips/year	8%
Travel group	Travel alone	35%
	Travel companions = 1	29%
	Travel companions = 2	12%
	Travel companions = 3	14%
	Travel companions = 4	7%
	Travel companions = 5	2%
	Travel companions = 6	1%
Travel with children	Yes	9%
	No	91%
Terminal use frequency	1-3 times/year	61%
	4-10 times/year	25%
	More than 10 times/year	14%
Wayfinding in terminal	Very difficult	4%
	Difficult	11%
	Moderate	19%
	Easy	38%
	Very easy	28%
Stress	Stress level = 1	30%
	Stress level = 2	29%
	Stress level = 3	18%
	Stress level = 4	17%
	Stress level = 5	6%
Fear	Fear level = 1	48%
	Fear level = 2	27%
	Fear level = 3	11%
	Fear level = 4	11%
	Fear level = 5	3%
Destination	Schengen	63%
	not Schengen	15%
	International	22%
Baggage	Hold baggage (yes)	54%
	Hand baggage = 0	3%
	Hand baggage = 1	72%
	Hand baggage = 2	20%
Trip_day	Weekday = Monday-Thursday	53%
	Weekday = Friday	21%
	Weekend	26%
Trip_plan	Plan activities before trip = yes	36%
	Plan activities before trip = no	64%

Table 2
Passenger categories according to purchasing behaviour and airport use.

		Revenue Range (€)	Average revenue per passenger (€)
Departing passengers	p_1 (33.1%)	0	0 €
	p_2 (16.8%)	(0, 8]	4 €
	p_3 (32.3%)	(8, 30]	19 €
	p_4 (17.8%)	>30	52 €
Arriving passengers	p_5 (87.8%)	0	0 €
	p_6 (12.2%)	>0	28 €
	p_7 (40.5%)	0	0 €
Transfer passengers	p_8 (42.0%)	(0, 32]	16
	p_9 (17.5%)	>32	48 €

transport (ride-hailing or taxi) are more likely to make no purchase compared to the other alternatives. For the group size, we found similar results to past studies (Freathy and O'Connell, 2012; Manzano, 2010). The impact of travelling alone is positive and higher for the utility of not making purchases (β_{alone_none}), followed by the utility of having few purchases ($\beta_{alone_{few}}$) as shown in past studies as well. Travelling with children also affected the behaviour of passengers; passengers travelling with children are more likely to make high purchases as the signs of the related parameters reveal ($\beta_{children\_none},\beta_{children\_few},\beta_{children\_medium}$).

The results confirm our assumption that passengers who pre-plan their activities are more likely to make purchases of any level at the terminal before departure compared to those who do not ($\beta_{planActivities\_none}$). We did not obtain information about the level of purchases as the results demonstrated that the was no improvement in the model when we considered alternative-specific parameters for the alternatives of few and medium purchases. This result is interesting as new technologies and mobile applications allow today passengers to have more control of their choices and determine early their airport experiences. Managers interested in increasing their non-aeronautical revenues could encourage the planning of passenger activities with the provision of pertinent information and, probably, mobile applications to the passengers.

Regarding the travelling behaviour of passengers, it was found that for a passenger who travels frequently by plane there is a higher probability of making medium or high purchases compared to few or none. It was also assumed and confirmed that it is more unlikely that passengers who travel for short stays make medium purchases compared to high ($\beta_{daysAway}$) and that people travelling for holidays would make purchases at non-aeronautical activities while no conclusion was made for other trip purposes.

The time of the day demonstrated some interesting results. Afternoon flights were more likely to induce purchases ($\beta_{afternoon}$) while for morning flights it was shown that it is more likely that passengers make few of medium purchases compared to high ($\beta_{morning\_few},\beta_{morning\_medium}$). Also, possible delays at the flight departure enhance medium and few purchases compared to high.

Contrary to what was expected, the type of airline and the number of baggage were not found to affect the level of purchases. This is different to knowledge established up to date and the reasons may be that airlines tend to adopt a low-cost behaviour for trips within Europe (ie. short duration flights) with the provision of minimum commodities on flights and the charging of any used service on board. The type of the airline we also expected to affect the level of purchases but aligned with past research (Choi and Park, 2022), we did not confirm such an assumption

Table 3
Parameter estimation of departing passengers' purchasing behaviour.

Parameter name	Associated variable description	Parameter value
$ASC_{nothing}$		2.060*
ASC_{few}		−1.410*
ASC_{medium}		−0.189
$\beta_{afternoon}$	1 if the departure is during afternoon in $V_{nothing}$	−1.100*
$\beta_{morning\_few}$	1 if the departure is during morning in $V_{fewPurchases}$	1.480*
$\beta_{morning\_medium}$	1 if the departure is during morning in $V_{mediumPurchases}$	0.668**
$\beta_{planActivities}$	1 if passenger has planned the activities to conduct before arriving at the airport in $V_{nothing}$	−1.080*
β_{car}	1 if passenger arrives by own car in $V_{nothing}$	−0.669***
$\beta_{personalised\_arrival}$	1 if passenger arrives by private personalized modes (taxi, tide-hailing) in $V_{nothing}$	−0.538***
β_{alone_none}	1 if passenger travels alone in $V_{nothing}$	0.848**
β_{alone_few}	1 if passenger travels alone in $V_{fewPurchases}$	0.672***
β_{age30_50}	1 if passenger is between 30 and 50 years old in $V_{nothing}$	−1.200*
$\beta_{age18\_22\_none}$	1 if passenger is between 18 and 22 years old in $V_{nothing}$	1.24**
$\beta_{age18\_22\_Few}$	1 if passenger is between 18 and 22 years old in $V_{fewPurchases}$	1.43**
$\beta_{age18\_22\_Medium}$	1 if passenger is between 18 and 22 years old in $V_{mediumPurchases}$	1.06***
$\beta_{age30\_50\_none}$	1 if passenger is between 30 and 50 years old in $V_{nothing}$	−1.030*
$\beta_{age30\_50\_few}$	1 if passenger is between 30 and 50 years old in $V_{fewPurchases}$	−0.352
$\beta_{age30\_50\_Medium}$	1 if passenger is between 30 and 50 years old in $V_{mediumPurchases}$	−0.813**
$\beta_{children\_none}$	1 if passenger is travelling with children in $V_{nothing}$	−1.650*
$\beta_{children\_few}$	1 if passenger is travelling with children in $V_{fewPurchases}$	−2.170*
$\beta_{children\_medium}$	1 if passenger is travelling with children in $V_{mediumPurchases}$	−1.940*
β_{delay_none}	1 if there was a delay in the departure in $V_{nothing}$	0.131
β_{delay_few}	1 if there was a delay in the departure in $V_{fewPurchases}$	1.070*
β_{delay_medium}	1 if there was a delay in the departure in $V_{mediumPurchases}$	0.739**
$\beta_{holidays}$	1 if passenger is travelling for holidays in $V_{nothing}$	−0.578***
$\beta_{highFrequency}$	1 if passenger travels by aircraft between 4 and 12 times per year holidays in $V_{nothing}$ and $V_{fewPurchases}$	−0.561**
$\beta_{incomeComfort\_none}$	1 if passenger has no economic difficulties in $V_{nothing}$	0.646***
$\beta_{incomeComfort\_few}$	1 if passenger has no economic difficulties in $V_{fewPurchases}$	0.745***
$\beta_{incomeComfort\_medium}$	1 if passenger has no economic difficulties in $V_{mediumPurchases}$	1.38*
$\beta_{daysAway\_medium}$	1 if passenger is travelling for 4 days or less	−0.860**
Number of observations		358
Estimated parameters		29
Null log-Likelihood (L(0))		−496.293
Log-Likelihood (L(β))		−411.948
ρ^2		0.170
Adjusted ρ^2		0.112

Notes: * Significant at 1%; ** Significant at 5%; *** Significant at 10%.
During the validation process, it was concluded that for 38% of the observations were correctly forecasted with a probability between 50% and 75% and 12% of the observations with a probability higher than 75%, using the reserved 20% data sampled for validation.

indicating that statements arguing that full air carriers contribute more to the non-aeronautical revenues than low-cost carriers are outdated.

Nested structured were also tested but did not prove to be better than the multinomial.

$$V_{nothing} = ASC_{nothing} + \beta_{afternoon} \times DepartTime + \beta_{planActivities} \times Preplanned_{Activities} + \beta_{car} \times CarArrival + \beta_{personalised\_arrival} \times PersonalisedArrival + \beta_{alone\_none} \times Travel_{Alone} + \beta_{age18\_22} \times Age_{18\_22} + \beta_{age30\_50\_none} \times Age_{30\_50} + \beta_{children\_none} \times Fly_{with_{kids}} + \beta_{delay\_none} \times Delay + \beta_{holidays} \times Holidays + \beta_{incomeComfort\_none} \times Income + \beta_{highFrequency} \times FlyFrequently$$

$$V_{fewPurchases} = ASC_{few} + \beta_{highFrequency} \times FlyFrequently + \beta_{alone\_few} \times Alone + \beta_{age18\_22\_Few} \times Age_{18\_22} + \beta_{age30\_50\_few} \times Age_{30\_50} + \beta_{children\_few} \times Fly_{with_{kids}} + \beta_{delay\_few} \times Delay + \beta_{incomeComfort\_few} \times Income + \beta_{morning\_few} \times DepartTime$$

$$V_{mediumPurchases} = ASC_{medium} + \beta_{age18\_22\_Medium} \times Age_{18\_22} + \beta_{age30\_50\_Medium} \times Age_{30\_50} + \beta_{children\_medium} \times Fly_{with_{kids}} + \beta_{delay\_medium} \times Delay + \beta_{morning\_medium} \times DepartTime + \beta_{daysAway\_medium} \times ShortStay + +\beta_{incomeComfort\_medium} \times Income$$

$$V_{highPurchases} = ASC_{high}$$

During the validation process, it was concluded that for 38% of the observations were correctly forecasted with a probability between 50% and 75% and 12% of the observations with a probability higher than 75%, using the reserved 20% data sampled for validation.

4.2.2. Arriving passengers

The results of passenger purchasing choices for arrivals is presented in Table 4. Passengers of the age group 30–50, passengers who are travelling on the cost of a company, have access to an airline's lounge and who arrive from non-Schengen origin airports are more likely to make purchases at the airport after arrival. On the contrary passengers who travel alone are more likely to make no purchase at the airport.

$$V_{NoPurchase} = ASC_{noPurchase} + \beta_{nonSchengen} \times nonSchengen + \beta_{alone} \times Alone + \beta_{group3} \times Group3 + \beta_{costsCompany} \times CostCompany + \beta_{age30\_50} \times Age30\_50 + \beta_{lounge} \times AirlineLounge$$

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.

4.2.3. Transfer passengers

The results of passenger purchasing choices for transfers is presented

Table 4
Parameter estimation of arriving passengers' purchasing behaviour.

Parameter name	Associated variable description	Parameter value
$ASC_{noPurchase}$		3.150
β_{alone}	1 if passenger travels alone	0.613***
$\beta_{costsCompany}$	1 if the cost of the trip is covered by a company	−0.715***
β_{lounge}	1 if the passenger has access to an airline's lounge	−3.500*
β_{age30_50}	1 if passenger is between 30 and 50 years old in $V_{NoPurchase}$	−0.973*
β_{Group}	1 if passenger is travelling with more than 3 people	−0.723**
$\beta_{nonSchengen}$	1 if the passenger arrives from a non-Schengen origin	−1.140*
Number of observations		487
Estimated parameters		7
Null log-Likelihood (L(0))		−337.563
Log-Likelihood (L(β))		−155.974
ρ^2		0.538
Adjusted ρ^2		0.511

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

in Table 5. Travelling in the morning impedes passengers from purchases before the flight while the stress felt to catch the flight, the access to airline lounges, the check of documents for flights outside the Schengen zone are aspects that do not favour higher levels of purchases.

$$V_{nothing} = ASC_{nothing} + \beta_{planActivities\_none} \times Preplanned_{Activities} + \beta_{age18\_22\_none} \times Age_{18\_22} + \beta_{age30\_50\_none} \times Age_{30\_50} + \beta_{afternoon\_none} \times DepartTime + \beta_{lounge\_none} \times AirlineLounge + \beta_{nonSchengen\_none} \times nonSchengen_{destination} + \beta_{stress\_none} \times Stress$$

$$V_{fewPurchases} = ASC_{few} + \beta_{planActivities\_few} \times Preplanned_{Activities} + \beta_{age18\_22\_few} \times Age_{18\_22} + \beta_{age30\_50\_few} \times Age_{30\_50} + \beta_{afternoon\_few} \times DepartTime + \beta_{lounge\_few} \times AirlineLounge + \beta_{nonSchengen\_few} \times nonSchengen_{destination} + \beta_{stress\_few} \times Stress$$

$$V_{highPurchases} = ASC_{high}$$

5. Application of gate assignment model to Lisbon Airport case study considering passenger purchasing choices

Terminal 1 of Lisbon airport is the scope of the current study (Fig. 2). The time interval 3pm–6pm of the 27th of August of 2019 was used for the application of the gate assignment optimization model. During this time interval, 22 flights were served by the airport. In total, Terminal 1 has 47 active gates, 33 of which were in use for flights in the considered time interval. Out of the 33 gates, 17 are connected to the terminal building with jet-bridges and the rest park in remote locations. Considering the restrictions imposed by the connecting countries, 22 of the served flights were links to Schengen points and 11 to non-Schengen, hence passport control facilities were required and consequently the allocated gates should consider this requirement (Table 6). Information on the gates was extracted from the application of the Lisbon airport which provides information only for the same day the attributed gates of the flights. Regarding the walking distances that passengers need to cover in the building including the distance from retail area to a certain gate (w_i^d) and from gate to baggage claim area (w_i^a), they were estimated using the aerial footage of the airport.

The non-Schengen gates that required a bus link (i.e. gates 10, 11, 13, 20, 22, 24, 25, 31 and 33), that were used and considered in the analysis, were considered to have the same w_i^a of gate 28, since it was considered that when arriving at the airport, the bus link always drops passengers near that gate. All gates can serve any aircraft, so g_i was considered to be 1 for all gates. A minimum time of free-gate was assumed to be 5 min (τ_i). The unloading time (δ_i) is the time the aircraft needs to arrive at the gate and allow passengers enter at the airport (or vice-versa, i.e. the time the aircraft needs to leave the gate after all passengers are on board); this depends if the gate has a jet-bridge or needs a bus connection. If there is a jet bridge the unloading time was assumed to be 5 min and in case of a bus connection, the unloading time was assumed to be 20 min. Besides, the time needed from runway to gate and from gate to runway, the distances were measured in Google Maps considering an average speed of 37 km/h. Finally, the minimum time intervals to allow a passenger

Table 5
Parameter estimation of transferring passengers' purchasing behaviour.

Parameter name	Associated variable description	Parameter value
$ASC_{nothing}$		2.510*
ASC_{medium}		2.140*
$\beta_{age18\_22\_none}$	1 if passenger is between 18 and 22 years old in $V_{nothing}$	1.920***
$\beta_{age18\_22\_few}$	1 if passenger is between 18 and 22 years old in $V_{fewPurchases}$	2.200**
$\beta_{age30\_50\_none}$	1 if passenger is between 30 and 50 years old in $V_{nothing}$	−1.050*
$\beta_{age30\_50\_few}$	1 if passenger is between 30 and 50 years old in $V_{fewPurchases}$	−0.007
$\beta_{afternoon\_none}$	1 if the departure is during the afternoon in $V_{nothing}$	−0.582
$\beta_{afternoon\_few}$	1 if the departure is during the afternoon in $V_{fewPurchases}$	0.880**
β_{stress_none}	1 if passenger stated stress level higher than 3 regarding travelling by aircraft n $V_{nothing}$	−1.510***
β_{stress_few}	1 if passenger stated stress level higher than 3 regarding travelling by aircraft in $V_{fewPurchases}$	−0.661*
β_{lounge_none}	1 if the passenger has access to an airline's lounge	−0.931***
β_{lounge_few}	1 if the passenger has access to an airline's lounge	–1.600*
$\beta_{nonSchengen\_none}$	1 if the passenger arrives from a non-Schengen origin in $V_{nothing}$	−0.754**
$\beta_{nonSchengen\_few}$	1 if the passenger arrives from a non-Schengen origin in $V_{fewPurchases}$	−0.846***
$\beta_{planActivities\_none}$	1 if passenger has planned the activities to conduct before arriving at the airport in $V_{nothing}$	−1.750*
$\beta_{planActivities\_few}$	1 if passenger has planned the activities to conduct before arriving at the airport in $V_{fewPurchases}$	−0.943***
Number of observations		279
Estimated parameters		16
Null log-Likelihood (L(0))		−306.513
Log-Likelihood (L(β))		−248.050
ρ^2		0.191
Adjusted ρ^2		0.139

Notes: * Significant at 1%; ** Significant at 5%; *** Significant at 12% level.
With this specification, 37% of the observations were correctly predicted by the model (with a probability higher than 50%).

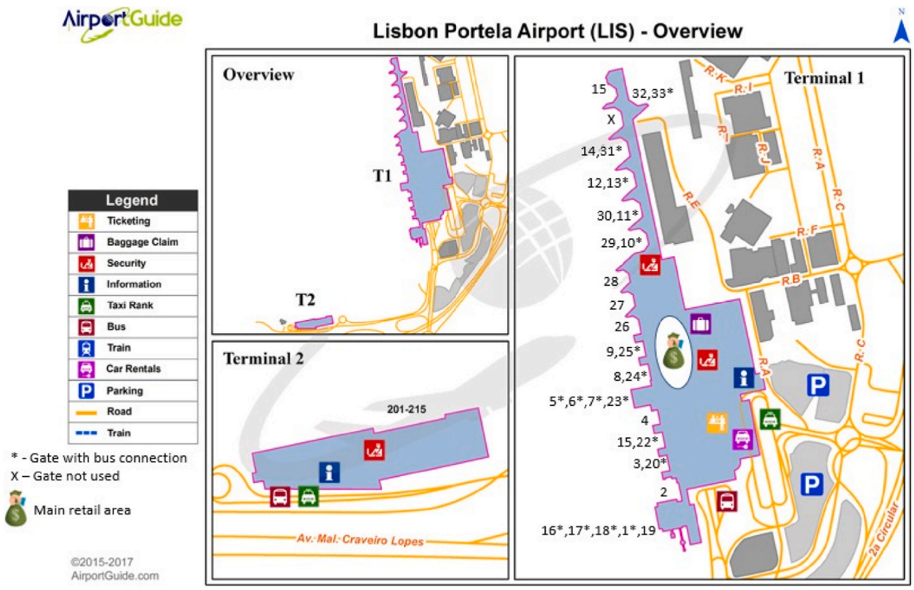

Fig. 2. Overview of lisbon portela airport (adapted from airport guide).

Table 6
Optimization framework.

Constant	Description	Value
NG	Number of Gates	33
NF	Number of Flights	22
NPC	Number of Passenger Categories	9
NTG	Number of Types of Gates	2

transfer to occur between two gates were considered (τ^t_{i,i_2}).

Regarding the flights, the 22nd and the 14th were identified as Schengen ($f^S_j = 1$) and 8 as non-Schengen ($f^S_j = 2$) due to their origin/destination. Moreover, 8 different airline companies and 21 origin/destination airports were included in the case study. Information regarding the actual arrival and departure times is also provided in Tables 8, 10, 12 and 14. Flights 11, 12, 13, 14 and 15 do not have any flight origin within the time interval analysed, as they were at the airport since the previous day, hence to include such situations in the model, 60 min to their departure time were subtracted. In addition, flights 8, 9 and 17 do not have any flight destination since they were expected to stay in the airport until the next day.

In Table 2, information regarding each expected revenue for the 9 different categories of passengers is provided. Initially, gates 8 and 24 were defined as the closest to the retail area, meaning that the obtained 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. The assumption that revenues decrease linearly with distance to the retail area in comparison with the farthest gate (gate 15) was made considering a maximum of 50% revenue decrease for the furthest gate. Hence, 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 (p_1), 2nd (p_2), 3rd (p_3) and 4th (p_4) passenger category, respectively. In the case of arriving passengers, the same assumption was made and gate 15 (0€ and 14€ for the 5th (p_5) and 6th (p_6) categories, 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 (p_5) and 6th (p_6) categories, respectively). In terms of transferring passengers, their revenues were simulated by taking into account only the gate of arrival, meaning that, similar to the arrival passengers, gate 15 (0€, 8€ and 24€ for the 7th (p_7), 8th (p_8) and 9th (p_9) categories, 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 (p_7), 8th (p_8) and 9th (p_9) categories, respectively).

Flights 8, 9 and 17 do not have any departing passengers since these aircrafts arrived at Lisbon airport within the time interval 3pm–6pm, but only executed another flight on the next day. Similarly, flights 11, 12, 13, 14 and 15 do not have any arriving passengers because their aircrafts were 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 aircraft, and the total number of transferring passengers from each flight is 10% of the mentioned capacity. Then, the arrival and departure time of each flight was compared and as mentioned in De Neufville et al. (2013), a transfer can only occur if there is a 60 min gap between flights. To increase this margin, since some gates need a bus connection, the minimum value between arrival and departure time was set to 120 min. Finally, regarding the possible passenger transfers, the total number of transfer passengers was randomly generated.

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, the cost of delay was found to be 72€/minute/aircraft according to De Neufville et al. (2013). Assuming a 100-seat capacity aircraft, each passenger has a cost of delay of 0.72€/minute. This value was assumed to be equal to the cost per minute travelled by passengers inside the airport. Then, a velocity of 60 m/min 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:

$$0.72\frac{€}{minute}\times\frac{1}{60}\frac{minute}{meter}=0.012\frac{€}{meter}$$

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

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

5.1. Gate allocation from 5pm to 5.30pm

Initially the problem had 353,754 variables but the pre-solved results show that the model is able to reduce the number of variables of the problem to 1.252, almost 283 times less. Thus, the model is able to solve the problem much faster than with the initial problem size. The solver found the optimal solution in 7.5 s, corresponding to a revenue of 23,371€. Table 7 presents the cost components of the optimal solution. As expected, the main source of revenues comes from revenues from departing passengers. Transferring passengers have the smallest impact in both revenues and cost of walking distance since they represent only 10% of each aircraft and lastly, arriving passengers have a bigger impact in the optimal solution.

Table 8 illustrates the results of the gate assignment model for the time interval from 5pm to 5.30pm. From flight 1 to flight 15, the model respects the previous attribution corresponding to flights being on the ground at the same time as this time horizon. Moreover, 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 it is already available.

5.2. Gate allocation from 5.30pm to 6pm

In this case, there is an a priori allocation of 18 flights (flights 1 to 18, all arriving before 5.30pm), and the mathematical model allocates the rest of the flights, 19 to 22, to achieve the best potential revenue. A computational time of 11.1 s was needed to achieve the optimal solution of 27,304.6 €. Using the same approach as before, the cost components of the optimal solution are presented in Table 9. The gate assignment results for this time horizon are also displayed in Table 10.

5.3. Gate allocation from 5pm to 6pm

This scenario allows to see the gate allocation when the mathematical model considers a time horizon of 1 h, from 5pm to 6pm. Thus, there is the a-priori gate allocation of flights 1 to 15, and the model assigns 7 flights (3 related to the 1st half an hour and 4 related to the 2nd half an hour to the respective gates). In this case, the optimal solution was computed in 41.6 s, with a revenue of 29,144.20€. The composition of the best solution in Table 11.

Lastly, the results are displayed in Table 12 where it can be confirmed that the model respects the Schengen/non-Schengen constraint and allocates the flights to the appropriate gates considering maximization of potential revenues.

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

This scenario illustrates 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 to 6pm as presented in Table 13. This extreme event consists of the scenario corresponding to an extraordinary event that gathers several people that will positively affect purchasing behaviour. More precisely, the potential passenger revenues increased in 8.0% and 12.2% on half an hour time horizon and 18.9% in a 1-h time horizon, reducing at the same time, the walking distance of passengers. Knowing this information a priori, the airport manager can achieve 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 14.

Similar to the previous scenario, the model allocates flights 15 to 22 in an optimal way. The optimal solution is computed in 45.8 s, with a revenue of 32,823.40€ (which was expected to be higher than the 'normal' time horizon from 5pm to 6pm since there are much more passengers willing to spend more money on flight 20).

Table 7
Demonstration of the optimal solution and its components from 5pm to 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	32,379.70
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	23,371.00

Table 8
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

Table 9
Demonstration of the optimal solution and its components from 5.30pm to 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	38,079.80
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	−10,709.30
Total	27,304.60

Table 10
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

Table 11
Demonstration of the optimal solution and its components from 5pm to 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	38,797.10
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	−10,053.30
Total	29,144.10

Table 12
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

Table 13
Demonstration of the optimal solution and its components from 5pm to 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	41,610.10
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	−10,076.30
Total	32,823.40

For the flights 16 to 22 in Table 14 and it is clear that comparing to Table 12, there is a change in the gate allocation of some flights (eg. 18, 20 and 22) showing that 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 study maximises airport revenues and consequently, the suggested framework can allocate flights to gates, considering all the variables, in the most profitable way. Finally, Table 13 intends to indicate the advantage of using this approach 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 passenger more willing to spend more money at the airport.

5.5. Comparison of suggested approach and actual planning

Table 15 demonstrates how the suggested approach can lead to economic benefits of an airport compared to the actual planning approach of gate assignment. An increase of 8.0% and 12.2%, corresponding to 1732.70 € and 2967.30 €, respectively, is achieved in a time horizon of half an hour using the exact mix of passengers. In practice, the announcement to passengers of what gate they need to go to is performed between every 15–30 min, and for this model, half an hour periods of gate allocation were adequate to the case study. The final model was then capable of performing half an hour gate allocation as showed in results, in just some seconds of computational time.

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. It is also possible to analyse the applicability of the model to 1-h time periods, in this case with an increase of 18.9%, corresponding to 4641.90 € in the total revenues.

Table 14
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

Table 15
Comparison between the actual planning to the mathematical model.

Revenue per time slot	Actual planning result	Mathematical model result	Variation
Gate allocation from 5pm to 5.30pm	21,638.30 €	23,371.00 €	+1732.70 € (increase of 8.0%)
Gate allocation from 5.30pm to 6pm	24,337.30 €	27,304.60 €	+2967.30 € (increase of 12.2%)
Gate allocation from 5pm to 6pm	24,502.30 €	29,144.20 €	+4641.90 € (increase of 18.9%)

6. Conclusion

Since airports' yearly budgets are more and more dependent on non-aeronautical activities, research related to the link of aeronautical and non-aeronautical operational issues is becoming more important. From the side of aeronautical activities, the gate assignment problem has been a constant challenge for airports and airline companies, due to the complexity arising from the involvement of the interests of many agents and operators (airport, airlines, passengers, retailers among others). Passenger purchases in the airport terminal, on the other hand, concern the management of non-aeronautical activities (in our case retail) and this kind of analysis can be included in gate assignment problems to reflect this link between aeronautical and non-aeronautical activities.

The objective of this study is the introduction of a modelling framework that could help airport managers to allocate flights to gates by maximizing the potential commercial revenues from passengers. A MILP gate assignment model was developed including passenger choice modelling, with the definition of a new objective function. This MILP assigns flights to gates considering all the constraints from gates and flights, by maximizing the money spent by passengers inside the terminal and at the same time ensuring minimized walking distances, using a conversion cost in order to achieve a final objective function with the same monetary units.

The results of the methodology application to the case study of Lisbon airport showed that the consideration of the passenger aspect in the gate assignment problem could have an impact on the non-aeronautical retail revenues of the airport under study. Although this impact in absolute numbers was not high, corroborating the conclusion of Dirk et al. (2020), when considering the numerical value, it is considerable for the management of non-aeronautical revenues.

The current work serves as a proof-of -concept of the potential of joining the two modelling approaches. It is suggested that future work focuses on the inclusion of further objectives and restrictions in the model related to aircraft operations and that the value of terminal gates is monetized according to the passenger purchasing behaviour at the neighbouring retail areas. Different types of passengers could also be defined and included in the passenger behaviour modelling while the relationship among purchase levels and distances could be explored in its various forms (such as linear, exponential among others). Mathematical formulas could be concluded for the relationship among distances and purchases to make future models more robust as in this study we made the assumption of a linear relationship to serve the purpose of this specific work. The use of more detailed data from airport operators could also enhance the methodological framework presented in this exploratory research; for example, a synchronous database of gate assignment and passenger behaviour could shed light on the impact of time availability on the purchasing behaviour and the consequent optimal gate assignment solution. Finally, other preferences of airport managers should also be considered and modelled. For instance, airport managers may prefer to avoid potential conflicts in taxiing and assign gates that are not close to each other at the same time, so that passenger do not get confused if their boarding gates and times are simultaneously too close.

Declaration of competing interest

None.

Acknowledgments

This work was supported by the Foundation for Science and Technology (FCT), through IDMEC, under LAETA, project UIDB/50022/2020. We would like to thank the anonymous reviewers for their valuable comments and recommendations that made us improve the quality of this manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jairtraman.2023.102452.

References

Appold, S.J., Kasarda, J.D., 2006. The appropriate scale of US airport retail activities. J. Air Transport. Manag. 12 (6), 277–287. https://doi.org/10.1016/j.jairtraman.2006.04.003.

Appold, S.J., Kasarda, J.D., 2011. Seeding growth at airports and airport cities: insights from the two-sided market literature. Res. Transp. Bus. Manag. 1 (1), 91–100. https://doi.org/10.1016/j.rtbm.2011.06.011.

Benlic, U., Burke, E.K., Woodward, J.R., 2017. Breakout local search for the multi-objective gate allocation problem. Comput. Oper. Res. 78, 80–93. https://doi.org/10.1016/j.cor.2016.08.010.

Bierlaire, M., 2003. BIOGEME: a free package for the estimation of discrete choice models. In: In*Swiss Transport Research Conference*.

Castaing, J., Mukherjee, I.A., Hurwitz, L., Nguyen, A., Müller, J.J., 2016. Reducing airport gate blockage in passenger aviation: models and analysis. Comput. Oper. Res. 65, 189–199. https://doi.org/10.1016/j.cor.2014.02.011.

Castillo-Manzano, J.I., 2010. Determinants of commercial revenues at airports: lessons learned from Spanish regional airports. Tourism Manag. 31 (6), 788–796. https://doi.org/10.1016/j.tourman.2009.08.005.

Castillo-Manzano, J.I., López-Valpuesta, L., González-Laxe, F., 2011. The effects of the LCC boom on the urban tourism fabric: the viewpoint of tourism managers. Tourism Manag. 32, 1085–1095. https://doi.org/10.1016/j.tourman.2010.09.008.

Castillo-Manzano, J.I., López-Valpuesta, L., Sánchez-Braza, A., 2018. When the mall is in the airport: measuring the effect of the airport mall on passengers' consumer behavior. J. Air Transport. Manag. 72, 32–38. https://doi.org/10.1016/j.jairtraman.2018.07.003.

Cheng, L., Fookes, C., Reddy, V., Yarlagadda, P.K., 2014. Analysis of passenger group behaviour and its impact on passenger flow using an agent-based model. In: 2014 4th International Conference on Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH). IEEE, pp. 733–738.

Choi, J.H., Park, Y., 2022. Exploring passenger and flight characteristics' impacts on airport retail income: evidence from Incheon International Airport. J. Retailing Consum. Serv. 66, 102913.

Chung, Y.S., Wu, C.L., Chiang, W.E., 2013. Air passengers' shopping motivation and information seeking behaviour. J. Air Transport. Manag. 27, 25–28. https://doi.org/10.1016/j.jairtraman.2012.11.006.

Crawford, J., Melewar, T.C., 2006. The importance of impulse purchasing behaviour in the international airport environment. J. Consum. Behav. 3 (1), 85–98. https://doi.org/10.1002/cb.124.

Daş, G.S., 2017. New multi objective models for the gate assignment problem. Comput. Ind. Eng. 109, 347–356. https://doi.org/10.1016/j.cie.2017.04.042.

Daş, G.S., Gzara, F., Stützle, T., 2020. A review on airport gate assignment problems: single versus multi objective approaches. Omega 92, 102146. https://doi.org/10.1016/j.omega.2019.102146.

De Neufville, R., Odoni, A.R., Belobaba, P.P., Reynolds, T.G., 2013. Airport Systems: Planning, Design, and Management. McGraw-Hill Education.

Del Chiappa, G., Bregoli, I., Fotiadis, A.K., 2021. The impact of COVID-19 on Italian accommodation: a supply-perspective. J. Tourism, Heritag. Serv. Market. (JTHSM) 7 (1), 13–22.

Dell' Orco, M., Marinelli, M., Altieri, M.G., 2017. Solving the gate assignment problem through the fuzzy bee colony optimization. Transplant. Res. Part C Emerg 80, 424–438. https://doi.org/10.1016/j.trc.2017.03.019.

Deng, W., Zhao, H., Yang, X., Xiong, J., Sun, M., Li, B., 2017. Study on an improved adaptive PSO algorithm for solving multi-objective gate assignment. Appl. Soft Comput. 59, 288–302. https://doi.org/10.1016/j.asoc.2017.06.004.

Dijk, B., Santos, B.F., Pita, J.P., 2019. The Recoverable Robust Stand Allocation Problem: a GRU Airport Case Study. OR Spectrum, pp. 1–25. https://doi.org/10.1007/s00291-018-0525-3.

Entwistle, M., 2007. Customer service and airport retail: stimulate passenger spending. J. Airpt. Manag. 1 (2), 151–157.

Eurocontrol, 2018. European aviation in 2040–challenges of growth. Available in: https://www.eurocontrol.int/publication/challenges-growth-2018.

Fakfare, P., Wattanacharoensil, W., Graham, A., 2021. Exploring multi-quality attributes of airports and the asymmetric effects on air traveller satisfaction: the case of Thai International Airports. Res. Transp. Bus. Manag., 100648 https://doi.org/10.1016/j.rtbm.2021.100648.

Fasone, V., Kofler, L., Scuderi, R., 2016. Business performance of airports: non-aviation revenues and their determinants. J. Air Transport. Manag. 53, 35–45. https://doi.org/10.1016/j.jairtraman.2015.12.012.

Frank, L., 2011. Business models for airports in a competitive environment. One sky, different stories. Res. Transp. Bus. Manag. 1 (1), 25–35. https://doi.org/10.1016/j.rtbm.2011.06.007.

Freathy, P., 2004. The commercialisation of European airports: successful strategies in a decade of turbulence? J. Air Transport. Manag. 10 (3), 191–197.

Freathy, P., O'Connell, F., 2012. Spending time, spending money: passenger segmentation in an international airport. Int. Rev. Retail Distrib. Consum. Res. 22 (4), 397–416.

Freitas, P.T., Silva, L.M., Nascimento, M.V., Borille, G.M., 2021. Passenger profile and its effects on satisfaction level in food and beverage establishments: case study of major Brazilian airports. Case Stud. Transport Pol. 9 (3), 1219–1224.

Fuerst, F., Gross, S., Klose, U., 2011. The sky is the limit? The determinants and constraints of European airports commercial revenues. J. Air Transport. Manag. 17 (Issue 5), 278–283. https://doi.org/10.1016/j.jairtraman.2011.03.001.

Geuens, M., Vantomme, D., Brengman, M., 2004. Developing a typology of airport shoppers. Tourism Manag. 25, 615–622. https://doi.org/10.1016/j.tourman.2003.07.003.

Graham, A., 2018. Managing Airports: an International Perspective, fifth ed. Routledge, New York. 9781138285347. https://www.routledge.com/Managing-Airports-An-International-Perspective/Graham/p/book/9781138285347.

Haghani, A., Chen, M.-C., 1998. Optimizing gate assignments at airport terminals. Transport.Res. Part -A 32 (No. 6), 437–454. https://doi.org/10.1016/S0965-8564(98)00005-6.

IATA (International Air Transport Association), 2014. Airport Development Reference Manual, ninth ed. Montreal, Canada. ISBN 92-9195-086-6. https://www.iata.org/en/publications/store/airport-development-reference-manual/.

Jiang, Y., Zeng, L., Luo, Y., 2013. Multiobjective gate assignment based on passenger walking distance and fairness. Math. Probl Eng. https://doi.org/10.1155/2013/361031, 2013.

Kalakou, S., Moura, F., 2021. Analyzing passenger behavior in airport terminals based on activity preferences. J. Air Transport. Manag. 96, 102110 j.jairtraman.2021.102110.

Kalakou, S., Moura, F., 2015. Modelling passengers' activity choice in airport terminal before the security checkpoint: the case of Portela airport in Lisbon. Transport. Res. Procedia 10, 881–890. https://doi.org/10.1016/j.trpro.2015.09.041.

Kalakou, S., Psaraki, V., Moura, F., 2015. Future airport terminals: new technologies promise capacity gains. J. Air Transport. Manag. 42, 203–212. https://doi.org/10.1016/j.jairtraman.2014.10.005.

Kim, S.H., Feron, E., Clarke, J.P., Marzuoli, A., Delahaye, D., 2017. Airport gate scheduling for passengers, aircraft, and operations. J. Air Transport. Manag. 25 (4), 109–114. https://doi.org/10.2514/1.D0079.

Kumar, P., Bierlaire, M., 2014. Multi-objective airport gate assignment problem in planning and operations. J. Adv. Transport. 48 (7), 902–926. https://doi.org/10.1002/atr.1235.

Lehto, X.Y., Cai, L.A., O'Leary, J.T., Huan, T.-C., 2004. Tourist shopping preferences and expenditure behaviours: the case of the Taiwanese outbound market. J. Vacat. Mark. 10 (4), 320–332.

Lim, A., Rodrigues, B., Zhu, Y., 2005. Airport gate scheduling with time windows. Artif. Intell. Rev. 24 (1), 5–31. https://doi.org/10.1007/s10462-004-7190-4.

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

Liu, X., Usher, J.M., Strawderman, L., 2014. An analysis of activity scheduling behavior of airport travelers. Comput. Ind. Eng. 74, 208–218. https://doi.org/10.1016/j.cie.2014.05.016.

Lu, J.L., 2014. Investigating factors that influence passengers' shopping intentions at airports - evidence from Taiwan. J. Air Transport. Manag. 35, 72–77. https://doi.org/10.1016/j.jairtraman.2013.11.009.

Mokhtarimousavi, S., Talebi, D., Asgari, H., 2018. A non-dominated sorting genetic algorithm approach for optimization of multi-objective airport gate assignment problem. Transport. Res. Rec. 2672 (23), 59–70.

Nikulin, Y., Drexl, A., 2010. Theoretical aspects of multicriteria flight gate scheduling: deterministic and fuzzy models. J. Sched. 13 (3), 261–280. https://doi.org/10.1007/s10951-009-0112-1.

Pant, P., 2022. Technology social practices by Millennials and Gen Z at airport departure terminals. Tourism Manag. Perspect. 43, 100978.

Puls, R., Lentz, C., 2018. Retail concessions at European airports: commercial strategies to improve non-aeronautical revenue from leisure travelers. J. Air Transport. Manag. 71, 243–249.

Rotondo, F., 2019. An explorative analysis to identify airport business models. Res. Transp. Bus. Manag. 33, 100417 https://doi.org/10.1016/j.rtbm.2019.100417.

Torres, E., Dominguez, J.S., Valdès, L., Aza, R., 2005. Passenger waiting time in an airport and expenditure carried out in the commercial area. J. Air Transport. Manag. 11 (6), 363–367. https://doi.org/10.1016/j.jairtraman.2005.04.001.

Tovar, B., Martin-Cejas, R.R., 2009. Are outsourcing and non-aeronautical revenues important drivers in the efficiency of Spanish airports? J. Air Transport. Manag. 15 (5), 217–220.

Tseng, W.C., Wu, C.L., 2019. A choice model of airline passengers' spending behaviour in the airport terminal. Transport. Plann. Technol. 42 (4) https://doi.org/10.1080/03081060.2019.1600243.

Vogel, H.A., 2011. Do privatized airports add financial value? Res. Transp. Bus. Manag. 1 (1), 15–24. https://doi.org/10.1016/j.rtbm.2011.05.002.

Wen, C.H., Wu, W.N., Fu, C., 2019. Preferences for alternative travel arrangements in case of major flight delays: evidence from choice experiments with prospect theory. Transport Pol. 83, 111–119. https://doi.org/10.1016/j.tranpol.2017.02.005.

Wu, C.L., Chen, Y., 2019. Effects of passenger characteristics and terminal layout on airport retail revenue: an agent-based simulation approach. Transport. Plann. Technol. 42 (2), 167–186. https://doi.org/10.1080/03081060.2019.1565163.

Young, S.B., 1999. Evaluation of pedestrian walking speeds in airport terminals. Transport. Res. Rec. 1674 (1), 20–26.

Yu, C., Zhang, D., Lau, H., 2016. MIP-based heuristics for solving robust gate assignment problems. Comput. Ind. Eng. 93, 171–191. https://doi.org/10.1016/j.cie.2015.12.013.

Yu, C., Zhang, D., Lau, H.Y., 2017. An adaptive large neighborhood search heuristic for solving a robust gate assignment problem. Expert Syst. Appl. 84, 143–154. https://doi.org/10.1016/j.eswa.2017.04.050.