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Airport Passenger Arrival Process: Estimation of Earliness Arrival Functions

Maria Nadia Postorino[a], Luca Mantecchini[b], Caterina Malandri[b]*, Filippo Paganelli[b]

[a]Mediterranea University of Reggio Calabria, Via Graziella, 89122, Feo di Vito (RC), Italy
[b]University of Bologna, Viale Risorgimento 2, 40136, Bologna (BO), Italy

Abstract

Airport terminals are complex nodes where passengers are processed under limited capacity conditions. Congestion problems and delays are likely to occur, with negative impacts on customer satisfaction. To keep high quality levels, the knowledge of passengers' arrival patterns is a key factor. In this study, a methodology based on the use of Bar Coded Boarding Pass (BCBP) technologies has been proposed to estimate arrival rate functions for different types of passengers (Low Cost and Full Carrier passengers) and time of the day. The results obtained for a test case have been analysed and discussed.

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Keywords: passenger arrival distribution; Bar Coded Boarding Pass; probability density function; security control.

1. Introduction

Airport passenger terminals are important processing nodes where the continuous flow of air travelers arriving from the airport catchment area is transformed into discrete departures, i.e. the scheduled flights. Within the terminal area, services such as check-in, passport and security controls, baggage drop, customs and baggage claim are provided to departing and arriving travelers (Ashford et al., 1997). All these operations are modeled as queuing processes characterized by service and waiting times.

Processes are organized in sequence and passengers queue at each step of the sequential processing chain until they receive the related service. Congestion problems and delays are likely to occur, particularly in large airports

* Corresponding author. Tel.: +39-329-563-7331.
E-mail address: caterina.malandri2@unibo.it
All the authors contributed equally to the work.

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where the number of processed passengers may be significant during peak hours. Moreover, queuing processes are unstable when capacity is almost reached, becoming unreliable and difficult to manage (De Neufville, 2016). In the light of passengers' perceived quality, check-in and security controls are the most crucial steps for departing travellers because long queues and waiting times increase the risk to miss the flight and then travellers' stress levels.

The right management of check-in and security control points – also identified as "resources" for the airport operator – has a twofold relevance. From one side, queues have a negative impact on customer satisfaction (Martin-Cejas, 2006), while high quality levels at server queuing nodes make the airport more attractive with respect to other competitive ones (Graham, 2005). On the other side, the right allocation of resources – for example, the number of check-in points or security control desks that should be opened to guarantee minimum processing times and then minimum queue length and delays – has a direct consequence on the airport cost saving (Kirschenbaum, 2013). For these reasons, capacity and space allocation in airport passenger terminals are among the most important issues for both airport design and operations. Furthermore, according to the International Air Transport Association (IATA), air passengers are expected to reach 7.8 billion by 2036 with a 3.6% average annual growth (IATA, 2017). If the trend is confirmed, unsatisfactory level-of-service at terminals are likely to increase. Therefore, airports should manage terminal facilities and adapt them to the growing demand in order to keep high quality levels and assure minimum waiting times for all the processing operations, though maintaining the required security level.

To design airport terminals, simulation models are among the most used tools because they make it possible to model queuing structures by replicating the operations of the real process and including implicitly variables such as human behaviour and attitudes. Simulation approaches have been widely used in the air transport field, particularly to analyse passengers' flow and queuing processes within airport terminals. Several studies have focused on check-in processes. For example, Lee et al. (2014) investigate the efficiency of self-service check-in desks in Singapore Changi Airport and, by using a simulation software, estimate the reduction in queuing and processing times due to the introduction of self-service check-in desks. In a similar study by Bevilacqua and Ciarampica (2010), the simulation approach is used to identify the number of check-in counters allocated to each departing flight and the management strategy to keep a good quality service. Some other studies have discussed security checkpoint processes. In Perboli et al. (2014), the software AirSIM is used to analyse the security system of an airport and identify suitable approaches to enhance the whole system performance. Van Boekhold et al. (2014) assess the operational performance of passengers and cabin baggage screening and, by using a microscopic simulation model, make a sensitivity analysis to investigate the effects of pre-screening. Only a few papers consider both processes as interconnected. Guizzi et al. (2009) develop a simulation model based on the discrete event theory to model passenger flow from entrance to boarding at Naples International Airport. The model may help to predict delays and to suitably model check-in and security checkpoints resources. Kalakou et al. (2015) model the effects of forthcoming changes at Lisbon Portela airport departure hall by estimating passenger expected processing times.

A common feature of all these approaches is the simulation of passenger arrival distribution. While flight schedules and average load factors for each flight are relatively easy to compute, passenger arrival distribution is not trivial, because it involves traveller behaviour, passenger segmentation and other context factors (de Lange et al., 2013). In fact, the passenger flow is not homogeneous (Ashford et al., 1997) since each passenger has specific needs and asks for specific services. Therefore, different peak characteristics are observed depending on whether the traveller is business or leisure, full-fare or special-fare, international or domestic, among the others. Moreover, dissimilar behavioural attitudes have been observed among different airports (Kim et al., 2004).

Even though it can be stated that passengers arrive at the airport from 4 hours to 1 hour before the departure of the flight (Malandri et al., 2017), intrinsic uncertainties remain depending on several factors such as the time of the day, the type of passenger and several others (van Boekhold et al., 2014). Moreover, the demand rate is not constant during those periods and unexpected peaks may affect negatively travellers' experience. Then, the knowledge of arrival distribution plays an important role to estimate the expected number of arriving passengers in smaller time intervals (ACRP, 2010).

The purpose of this work is to estimate probability density functions describing passengers' arrival pattern at security checkpoints, which may be considered the "bottleneck" of the terminal system and the process generating the highest delays (Kierzkowski and Kisiel, 2017). Bar Coded Boarding Pass technologies are included as important part of the proposed methodology to collect real-time data allowing estimating passenger arrival rate functions. The knowledge of such functions is crucial to identify expected passenger flows and to evaluate the amount of space and the number of servers required for each airport sub-process. To this goal, real-time data collected at security checkpoints are used to estimate different arrival rate functions depending on the air company (Low-cost Carrier, LCC, vs. Full Carrier, FC) and the scheduled flights (early morning vs. late afternoon periods). This segmentation allows verifying whether different behaviours are revealed depending on passenger type (LCC vs FC passengers) and time of the day (early morning vs. late afternoon).

The remaining of the paper is organized as follows. Section 2 describes the methodology used to derive the probability density functions describing passengers' arrivals. Section 3 discusses the results for the case of Bologna "Marconi" Airport, while Section 4 reports some concluding remarks.

2. Methodological framework

The identification of the probability function describing passengers' arrivals at medium-sized airports represents a central step in the process of airport terminal facilities management (Figure 1). In fact, right estimates of passenger flows allow verifying whether the resources allocated at security control areas are suitable and how to manage properly the system. When such estimates are not available, the risk of unsuitable resources allocation – which may damage the involved stakeholders (airport operators, passengers, airlines) – is high.

Outcomes of the proposed approach are probability density functions, which describe passenger flows at checkpoints as a function of the time of the day and passenger type (LCC vs. FC). More in detail, continuous probability functions – describing how much in advance passengers arrive at checkpoints with regard to the expected take-off time of their flight – are estimated by using data collected at security control desks. Such functions may be used as input for simulation models and to forecast scenarios. In these authors' knowledge, the literature in the last decade is lacking about such kind of studies, which try to reduce the gap between data collection/simulation and management issues.

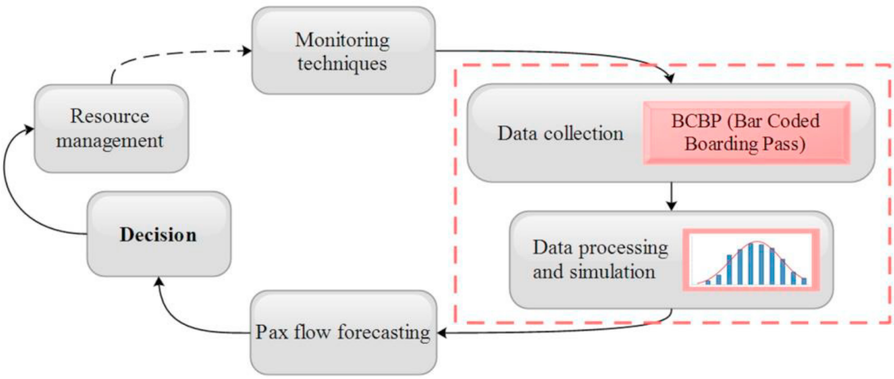

Figure 1. Data collection and processing to improve airport resource management

In order to derive arrival profiles, security control desks for departing passengers have been used as checkpoints. The choice of security control desks to collect data depend on the fact that they represent the first, unavoidable barrier for all departing passengers. In fact, all travellers have to undergo security controls, while some passengers may not need to present at check-in desks – for example, the ones who use check-in online and do not need to register any baggage. Then, data collected at security control desks include the whole set of passengers who are going to board a plane in a given time interval.

The methodology described here is based on the use of Bar Coded Boarding Pass (BCBP) technologies, which allow automatic detection of data. BCBP technologies have been introduced by the program "Simplifying The Business" (IATA, 2010), which suggests the use of 2-dimensional barcodes on boarding passes, either printed or shown on mobile devices.

When arriving at security checkpoints pre-queue area (Figure 2), all passengers must present their boarding card to proceed further. By using BCBP systems, real-time data are collected by scanners reading the barcode of both paper and mobile boarding cards. Key data encompass flight information (such as airline, destination, expected departure time) as well as the time the passengers scan their card under the reader – which is the crucial information for this study. All personal data are excluded from storage or processing because of privacy reasons. It is worthwhile to note that manual counts could also be possible. However, manual counting has several disadvantages because the quality of data depends on staff experience, while BCBP systems detect data at high and constant quality levels (nearly 100% accuracy).

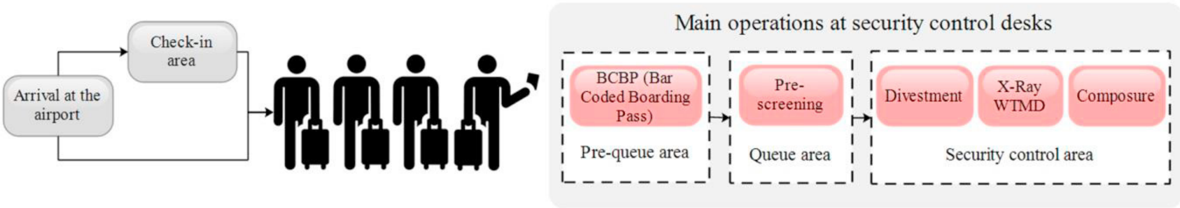

Figure 2. Main operations for departing passengers

BCBP scans can be compared with actual flights data available from the airport operation database in order to compute the difference between the scheduled time of departure and the time the passenger scans the boarding pass at the processing point. This information – i.e. the earliness arrival – obtained from all passengers provides travellers' behaviour profile as for arriving time.

For each passenger i, the Early Scheduled Delay (ESD_i) – i.e. how much in advance passengers arrive at checkpoints – is obtained as the difference between the Scheduled Time of Departure (STD_i) of the flight and the time at which the passenger scans the boarding card under the reader ($BCBPT_i$):

$$ESD_i = STD_i - BCBPT_i \tag{1}$$

Data are aggregated over time intervals of 15 minutes (time block). The discrete arrival distribution is obtained by computing the number of passengers arriving in each earliness time block. From the discrete earliness arrival data, the underlying probability density, which describes the arrival process, can be identified by testing probability density functions and identifying the best one by the Chi-Square (χ^2) test (Judge et al., 1985). The estimated probability density function can then be used to forecast passenger flows for selected periods Δt. Particularly, the number of expected passengers at security checkpoints depend on the passenger earliness aptitude as regards their *STD*. Then, the number of expected passengers of flight j, P_j, who arrive in the time interval Δt is given by:

$$P_j^{\Delta t} = N_j \int_{\Delta t} f(x)dx \tag{2}$$

where x identifies the Early Scheduled Delay *ESD;* $N_j=C_j \cdot LF_j$ is the expected number of passengers boarding flight j; C_j is the aircraft capacity and LF_j is the average load factor of flight j.

The total number of expected passengers *TP* arriving in Δt at security control checkpoints is then given by:

$$TP^{\Delta t} = \sum_j P_j^{\Delta t} \tag{3}$$

Results from equations (2) ad (3) make it possible to identify peak demand and peak periods.

The proposed methodology may help airport operators to evaluate the service quality level, compute performance indicators and then identify critical periods when resources should be allocated to maintain high standards and improve passenger experience. Furthermore, based on the expected passenger arrival rate, airport operators can plan effective staff scheduling and deploy appropriate resources reflecting real customer needs.

3. Results

The methodology described in the previous section has been applied to Bologna "Marconi" Airport, a large regional airport located in Northern Italy with approximately 72 thousand movements and 8.2 million passengers in 2017, with 24 available boarding gates.

The detection system at Bologna security control checkpoints collects a large amount of data concerning number of arrivals, queue waiting time and queue length. More in detail, to access the so-called snake area (zone A in Fig. 3), passengers must go through one of the several accessing gates where the bar-coded boarding card is read. This first check of the boarding card allows pinpointing the arrival time – and then how much in advance passengers arrive at the security control checkpoints depending on the scheduled departure time of their flight. Once crossed the accessing gates and walked to the end of the snake area, nine security control lines are available (zone B, in Fig. 3). Before each control point, a device called "Logiscan" verifies the size of the cabin baggage and to this goal the boarding card is read again. The second check of the boarding card allows measuring the time spent in the snake area by each passenger.

Data used to estimate the arrival distribution functions – kindly made available by the airport operator – refer to passengers arriving at security control checkpoints and registered during a winter peek week (17 - 23 December).

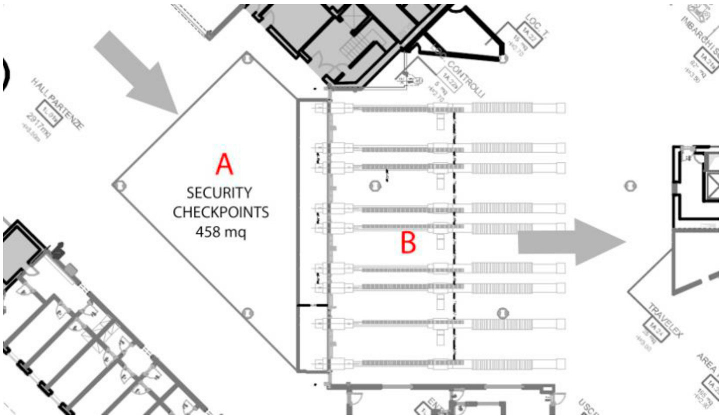

Figure 3. Layout of the security control zone. A: queue area ("snake"); B: security lines (Courtesy: Bologna Airport)

Table 1. Travel characteristics associated to the examined sample of departing passengers

	Airline	Flight n°	Type	Destination	Scheduled departing time
Early morning	Ryanair	FR4798	LCC	Domestic	6:35 am
	Lufthansa	LH291	FC	EU Schengen (International)	7:00 am
	British Airways	BA543	FC	EU extra Schengen (International)	7:10 am
Late afternoon	British Airways	BA545	FC	EU extra Schengen (International)	6:35 pm
	Lufthansa	LH289	FC	EU Schengen (International)	7:00 pm
	Ryanair	FR4341	LCC	Domestic	7:30 pm

Table 1 reports the main travel characteristics of the detected passengers used to estimate the arrival rate functions, which have been obtained for two main periods: 1) early morning; 2) late afternoon. The underlying hypothesis is that passenger arrival behaviors may change among different periods and then these two extreme points – early morning and late afternoon – have been considered. Furthermore, security control times may also depend on the destination (e.g., domestic *vs.* international) and then the most usual cases have been considered (in the case of Bologna airport, domestic, EU Schengen and EU extra-Schengen).

Based on the χ^2 test, the Weibull function resulted the best one for describing the arrival processes among other tested functions (Gauss, Poisson, Gamma, Lognormal):

$$f(x) = \frac{\beta}{\alpha^\beta} x^{\beta-1} \cdot \exp\left[-\left(\frac{x}{\alpha}\right)^\beta\right] \tag{4}$$

where x is Early Scheduled Delay *ESD*, α and β are parameters whose estimated values have been reported in Figure 4. In the same figure, continuous and dashed lines refer to the estimated Weibull functions respectively for FC and LCC services, while histograms refer to real data, again for FC (grey coloured) and LCC (black coloured) services.

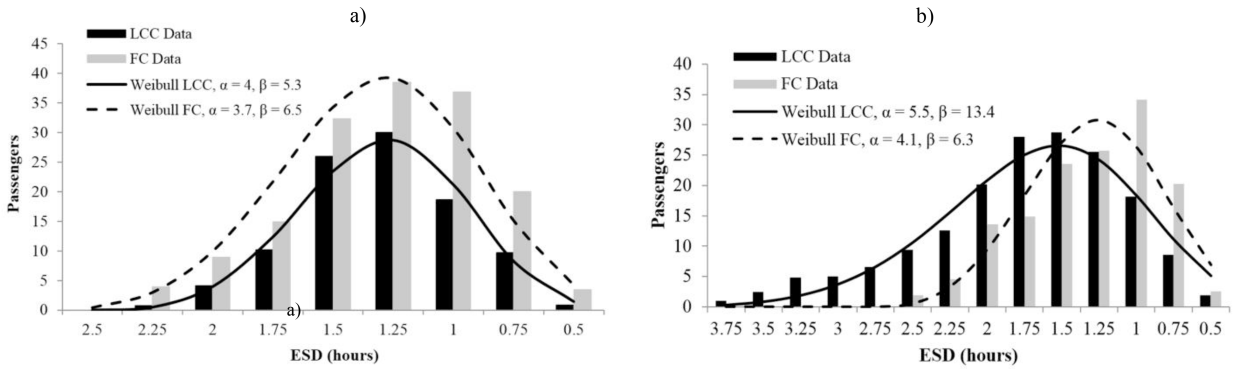

Figure 4. LCC and FC passenger arrival function, early morning (a) and late afternoon (b)

As for carrier type (LCC *vs.* FC), data show that during the morning period (Figure 4a) about 85% of FC passengers arrive at security control checkpoints closer to the expected departing time of their flight. Particularly, most part of passengers arrive about 60-90 min before their scheduled flight, while 13% of passengers arrive only 30 min before the scheduled departure time. This is common also to LCC passengers. However, during the late afternoon period (Figure 4b) LCC passengers are spread over a much wider arrival time interval, while FC behaviours are almost similar as in the early morning – most part of passengers arrive about 60-90 min before their scheduled flight. Both in the morning and in the afternoon, FC arrival peaks correspond to an *ESD* in the range 60-90 min. This passenger behaviour is probably due to FC characteristics, particularly fidelity programs and business services assuring some suitable facilities – such as access to the business lounge and reserved gate boarding as well as fast track points at security control desks – which give passengers privileged access during congested periods thus reducing their *ESD*.

The scheduled departure time plays also a significant role. In fact, passengers boarding in the early morning arrive closer to the scheduled departing time of their flights than late afternoon passengers, depending mainly on their expected time to access the airport (in the early morning there is no significant congestion delay as regards the late afternoon) and the facilities offered at the airport (not all shops in the retail area are open in the early morning).

From eq. (2) and the estimated arrival functions – both for FC and LCC – the expected number of departing passengers has been computed during the period 6:00 – 8:00 am for a typical late winter Monday, with Δt=15 minutes. The expected number of passengers of each flight j, $N_j=C_j \cdot LF_j$, has been computed by assuming an average load factor *LF* of 0.88 for LCC and 0.70 for FC, according to data provided by the airport. As for capacity *C*, the number of offered seats for each flight – depending on the aircraft type – has been considered. Table 2 shows the results for the 16 departing flights scheduled in the selected period.

Finally, the histogram in Figure 5 shows the arriving passenger flow trend during the considered period (6:00 am – 8:00 am), estimated by means of eq. (3). The maximum estimated passenger arrival rate in the considered period is between 5:00 am and 5:30 am, when about 1,000 departing passengers are expected at security control checkpoints, in line with data available at Bologna airport.

Table 2. Predicted arriving passengers at security checkpoints for each flight scheduled between 6:00 and 8:00 am

Flight n°	Departure	03:30	03:45	04:00	04:15	04:30	04:45	05:00	05:15	05:30	05:45	06:00	06:15	06:30	06:45	07:00	07:15	07:30	07:45	08:00
FR195	**06:20**	0	0	1	7	21	39	48	35	14	2	0								
FR4338	**06:25**	0	0	1	7	21	39	48	35	14	2	0								
KL1582	**06:30**	0	0	2	6	11	16	18	16	10	4	1	0							
BV2552	**06:30**	0	0	0	1	7	21	39	48	35	14	2	0							
EN8245	**06:30**	0	0	2	5	11	16	18	15	9	4	1	0							
FR4324	**06:35**	0	0	0	1	7	21	39	48	35	14	2	0							
FR4798	**06:35**	0	0	0	1	7	21	39	48	35	14	2	0							
FR9982	**06:50**	0	0	0	0	1	7	21	39	48	35	14	2	0						
LH291	**07:00**	0	0	0	0	2	6	13	19	21	18	11	5	1	0					
IB8785	**07:00**	0	0	0	0	2	5	9	13	15	13	8	3	1	0					
AF1029	**07:00**	0	0	0	0	2	6	12	18	20	17	11	4	1	0					
AZ1312	**07:15**	0	0	0	0	0	3	8	15	22	25	22	13	6	2	0				
FR6423	**07:15**	0	0	0	0	0	0	1	7	21	39	48	35	14	2	0				
BA543	**07:40**	0	0	0	0	0	0	3	8	15	23	26	22	14	6	2	0			
OS536	**07:40**	0	0	0	0	0	0	0	2	6	13	19	21	18	11	5	1	0		
NO1446	**08:00**	0	0	0	0	0	0	0	0	3	9	17	25	29	24	15	6	2	0	
TOT PAX		0	0	6	28	92	200	316	366	323	246	184	130	84	45	22	7	2	0	0

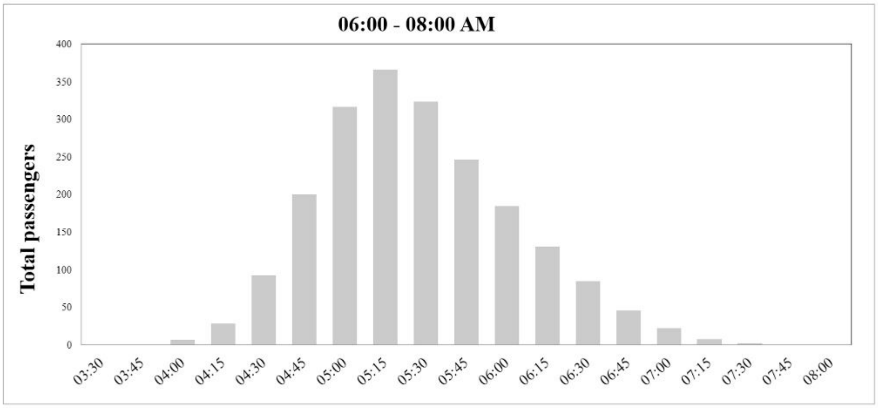

Figure 5. LCC and FC passenger arrival functions, 6.00 am – 8.00 am scheduled flights

4. Main findings and conclusions

The use of BCBP technologies allows obtaining a great amount of reliable data concerning, for the purposes of this paper, passenger arrival times at security control checkpoints. Such data can be used to estimate arrival rate functions, which in turn can be used to obtain the expected number of passengers arriving in prefixed time intervals depending on the number of scheduled flights during the considered period. This combined use of technologies and mathematical issues represents a suitable ITS to plan a more efficient use of airport resources and manage them accordingly.

By using real data collected at Bologna airport in early morning and late afternoon periods for airline types (LCC, FC) and destinations, arrival rate functions have been estimated in order to predict passenger arrival rates during morning and afternoon and also verify the existence of different behaviours between LCC and FC passengers. The results show that in the early morning period there are no significant differences between LCC and FC passengers.

Particularly, both kinds of passengers arrive mostly 60-90 min before their scheduled flights (about 70%), while the remaining percentage is distributed between very early arrivals (2 hours and more before the scheduled flight) and rather late arrivals (30 min before the scheduled flight). In the late afternoon period, while the FC function has still similar characteristics, the LCC function is spread over a greater period. Particularly, a significant percentage of passengers arrive at security control checkpoints more than 120 min before the time of their scheduled flight. The different behaviour depends on: FC and LCC features, mainly fidelity and privileged access issues; airport accessibility during the day in line with the transport system serving the area; airport facilities, mainly shop availability during the day.

These first results can be considered a starting point for further analysis and modelling. Particularly, developments are expected by using larger samples of data coming from several airports using similar BCBP technologies in order to simulate explicitly passenger's behaviour depending on airline, airport accessibility and facilities. In addition, larger data set will allow testing several hypotheses about the mathematical modelling of the arrival processes.

Acknowledgements

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