SIMULATING BOARDING STRATEGIES FOR MINIMISING PASSENGER AIRCRAFT TURN-TIMES

Luis Cadarso[(a)], Nuria Perelló[(b)], Angel A. Juan[(c)], Javier Faulin[(d)]

[(a)] Rey Juan Carlos University, Madrid, Spain
[(b)] Autonomous University of Barcelona, Barcelona, Spain
[(c)] Open University of Catalonia, Barcelona, Spain
[(d)] Public University of Navarre, Pamplona, Spain

[(a)]luis.cadarso@urjc.es, [(b)]nuria.perello@gmail.com, [(c)]ajuanp@uoc.edu, [(d)]javier.faulin@unavarra.es

ABSTRACT

The airline industry implements many simulation models to optimise its operations, knowing that small changes in the policies of its companies involve significant improvements in the long run. Here, we have developed some simulation models to make a comparison between different boarding strategies for passengers in an A380 aircraft. After suggesting six different strategies (back-to-front, outside-inside, optimization, by blocks, random, and alternative rows) and having performed the apposite simulation models and their corresponding ANOVA analysis, the alternative rows strategy has revealed as superior in relation to the other strategies. Some final considerations have also been discussed about the limitations of each strategy and the goodness of the proposed as the better.

Keywords: Simulation, Boarding Strategy, Turn-time, Passengers Air Transport

1. INTRODUCTION

The airline sector is a highly competitive industry where each airline must struggle to win a suitable position in the market. In order to increase the associated profitability, the greatest efforts are focused on optimising operational processes controlled by the airline companies such as the use of available resources.

The wild competition between airlines (especially between legacy and low-cost airlines) and the current fuel prices generate small profitability margins, being sometimes negative. Therefore, airlines are always interested on maximizing resources usage. Increasing aircraft utilization, for example, allows the airlines to serve more origin-destination routes and to place more frequencies on them, thus serving more passengers and capturing greater revenues. Reducing the time an aircraft spends on the ground increases profit (Ferrari and Nagel, 2004; Van Landeghem and Beuselinck, 2002, Lewis and Lieber, 2005): an aircraft in the ground does not generate any revenue (Van de Briel et al., 2005) but does airport fees. According to Van Landeghem and Beuselinck (2002) the turn-time of an aircraft (i.e., the elapsed time in ground with the chocks placed) is about 30-60 minutes (i.e., it depends on the aircraft size). Each minute an airline spends during the boarding process costs \$30: for an airline operating a flight network with 500 daily flights, a decrease of a single minute for all the turn-times results in annual savings of \$5,475,000 (Nyquist et al., 2008).

Therefore, the process of passenger boarding is a key step during the turn-time of an aircraft. Based on the airline tradition and the level of service it wants to offer, a specific boarding strategy is chosen (Van de Briel et al., 2005). Factors such as the speed of passengers, the amount of hand luggage they carry on, and the interference that may exist for each strategy should also be taken into account in order to be efficient. Furthermore, the robustness of the strategy should not be neglected because many of them are efficient but few are robust when implemented. The most common strategies among legacy airlines are *back-to-front* and *outside-inside*. They are also used in a hybrid way.

This paper focuses on the study and comparison of different strategies used for boarding passengers in medium to long haul flights operated by the A380 fleet type. We focus on the optimization and improvement of the boarding process, neglecting the events out of control of the airline. There are two main reasons why this study is carried out: (1) there are few studies on boarding strategies for large aircraft types since other authors have focused on optimizing the process for smaller fleet types; and, (2) we think it is more important to study boarding strategies for larger aircraft types due to the number of passengers, the existence of more than one aisle and boarding gates and sometimes two decks. These factors make the boarding process more complex: more interference arise as compared to smaller aircraft types such as those ones with a single door, aisle and deck. Furthermore, as passengers may usually carry on more than one hand luggage in the flights served by this fleet type, the difficulty for reaching an efficient and smooth boarding process is greater.

2. STATE OF THE ART

The passenger boarding process has been studied by many other researchers. Most of the past studies focus on the simulation rather than in an analytical approach. Marelli et al. (1998) developed a simulation model in order to study different strategies under different configurations of a Boeing 757 for boarding and deboarding of passengers. Van Landeghem and Beuselink (2002) explored different patterns of boarding; Van den Briel et al. (2003, 2005) studied the boarding problem using integer programming, non-linear assignment models and simulation models with real data samples. Ferrari (2005) used different schemes to evaluate different boarding strategies and designed a new model consisting of boarding small groups; they concluded that the most efficient strategies were separating groups traveling together, thus decreasing passenger satisfaction. Van Landeghem and Beuselinck (2002) reached similar conclusions to those ones in Ferrari and Nagel (2005).

Bazargan (2007) analyzed the interferences between passengers causing greater boarding times and designed an integer programming model to minimize these interferences. Nyquist and McFadden (2008) analyzed the most effective boarding strategies in terms of costs while also accounting for customer satisfaction. Steffen (2008) used simulation to study the sequencing of passengers to minimize the boarding time. Steiner and Philipp (2009) built a simulation model and used samples of observations drawn from the Zurich airport to calibrate the model; they accounted for various actions carried out in and out of the aircraft.

Thus, the main contributions of this paper are summarized as follows: (a) we have developed a simulation model to replicate the different boarding strategies in an A380 aircraft with the purpose of finding the lowest boarding time strategy; and (b) we have tested the previous optimal strategy with realistic instances in the aforementioned A380. In this way, we use simulation models to make decisions with optimization objectives.

3. PROBLEM DESCRIPTION

In this section, the boarding problem is described in detail. First, the boarding process is presented. Then, the different boarding strategies are introduced.

3.1. The Boarding Process

The boarding process is one of the processes included in the set of activities that are performed during the turnaround of an aircraft; the turnaround begins when an operator puts ramp chocks and finishes when the aircraft pushback starts.

During the turnaround of an aircraft, besides the passenger boarding process, other activities are carried out, such as baggage unloading and loading, visual inspections of the aircraft, cleaning, fuelling, and catering. The handling of these services may be done by the airport itself, or by specific companies specialized in handling services (which may be owned by the airline, the airport or any other entity). The speed, accuracy and efficiency provided by these handling companies are key factors to minimize the overall turn-time. Most of these activities can be made while other activities are being performed. However, there are activities such as deboarding and boarding of passengers that cannot be performed in parallel. Figure 1 shows the different activities to be carried out during the turnaround.

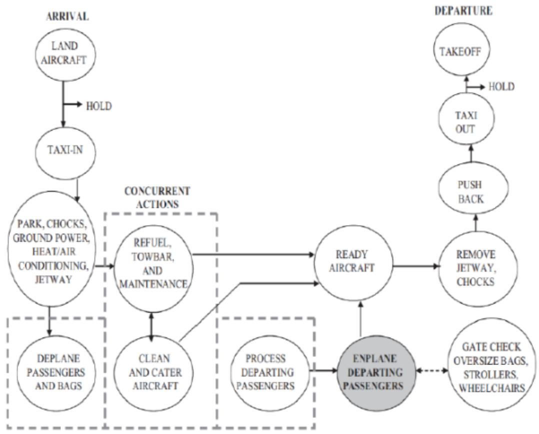

Figure 1: Turnaround process for a passenger aircraft

The total boarding time depends on factors such as the size of the aircraft, airport infrastructure, ground handling services, human resources workload, hand luggage or passenger behaviour. Some of them are controllable while others not.

The boarding process is composed of three different steps:

1. announcement: the boarding start is announced to the passengers and passengers queue at the gate;
2. check in: an airline agent checks all boarding passes and registers passengers into the system;
3. and access: passengers access to the aircraft through the finger or by bus. In the latter case, passengers arrive at the door of the aircraft in large batches. Once inside the aircraft, passengers queue in a straight line in order to reach their assigned seat.

There are several causes of delays during the boarding process such as late arrival of passengers (e.g., delayed connecting passengers), malfunction of electronic systems used during the boarding, removal of excess baggage in the gateway (due to the strengthening of control over luggage limits) and passenger behaviour (i.e., storage of hand luggage and sitting down). Some of these delays are increased due to the nature of some flight networks such as hub-and-spoke networks.

3.2. Boarding Strategies

There is no a universal strategy which is efficient for every boarding that is performed around the world.

Each airline must ensure that its strategy reaches a trade-off between the multiple different objectives, such as the level of service offered to the passengers, the flexibility to the characteristics of the aircraft, the load factor of the flight and the early and/or late arrival of the passengers. Furthermore, there are also external factors affecting the suitability of each one of the strategies such as the availability of fingers and multiple aircraft doors.

The most employed strategies by legacy airlines are: *back-to-front* and *front-to-back*, *outside-inside*, *optimization*, *by blocks*, *random* and *alternating rows*. We describe each of the strategies in the following subsections.

3.2.1. Back-to-front and front-to-back

Back-to-front is the most often used strategy by the majority of the small and large fleet sized airlines. In this strategy, first class boards first and then the rest of the passengers are called to board by groups, following a sequence from the back to the front of the aircraft.

It is the most common strategy due to its simplicity and ease to be understood. Also, it allows groups of passengers traveling together to board at once. As disadvantages, there is no evidence that it is the most efficient strategy and there are large interferences between the passengers.

Front-to-back is the opposite strategy, i.e. first class boards first and then the rest of the passengers are called to board by groups, following a sequence from the front to the back.

3.2.2. Outside-inside

The *outside-inside* strategy, also known as *Wilma* (window-middle-aisle), consist of boarding passengers as follows: first class passengers, passengers who are assigned a seat next to the window, then middle seats and finally aisle seats. The advantages of this strategy are that it has less interference and if the boarding is successfully conducted, seat interferences are completely eliminated. The main disadvantage is that this strategy forces passengers traveling together to board separately and during different time periods.

3.2.3. Optimization

It consists of first boarding passengers with a window seat, followed by those in the middle and finally the aisle seats; passengers board diagonally in this strategy. Thus, it can be considered a hybrid strategy between *back-to-front* and *Wilma* strategies. This strategy boards passengers traveling together at once.

3.2.4. By blocks

This strategy consists of boarding passengers sitting in the middle of the aircraft at the last place. The passengers are grouped by areas and are boarded as follows: first the area of the front, then the one at the rear and again an area from the front and so on; therefore, the strategy rotates from the front to the rear. The first class is always boarded first.

3.2.5. Random

The *random* strategy accommodates passengers randomly so there is only one area. The first class passengers board first, and then the rest of the passengers with assigned seats are boarded. This strategy is known as FIFO (first in-first out).

3.2.6. Alternating rows

In this boarding strategy, first, all passengers sitting in the window seats on one side of the plane board at once, in alternating rows (rows 1, 3, 5, etc.). Then the same is done on the other side of the plane. Then the middle seats, still in alternating rows, board on the first side of the plane. That continues with the other side's middle seats, then aisle seats (first one side and then the other one). Then, the process is repeated for the even-numbered rows.

It is simple, but very efficient; alternating rows gives everyone enough elbow room; taking careful notice of seat position it reduces bottlenecks from aisle-passengers having to stand up all the time.

4. SIMULATION MODEL

The simulation model makes the following assumptions:

1. passengers are assigned to seats randomly;
2. seats are classified into different groups;
3. and passengers within the same group board the aircraft randomly.

The following subsections describe the passenger behaviour and the aircraft and load factor influences on the process.

4.1. Passenger Behaviour

Once inside the aircraft, each passenger goes to his/her seat based on his/her walking speed (walking time per seat row). Obviously, he/she will stop if another passenger obstructs his/her way. We assume that passengers are not mistaken about their seats and, therefore, they go the right way when reaching their seats. In addition, passengers have an associated delay time to get to the seats because they need a certain time to locate their hand-luggage in the upper compartments (hand-luggage time); we assume every passenger carries hand-luggage. Moreover, when a passenger reaches the seat row where he/she is sitting, if there is another sitting passenger, we assume that some time is needed to wait for this passenger to clear the way for the incoming person (interference seating time).

We have relied on the study by Mas et al. (2012) in order to determine the passengers' parameters. They observed several real boarding processes and obtained realistic values for parameters such as the walking time per row, delays caused by passengers' interferences, or the time associated with luggage handling inside the plane. We assume the following values are constant and read as follows:

1. walking time per row equals to one time period (i.e., one time period represents half a second);

2. interference seating time equals to ten time periods;
3. and hand-luggage time equals twelve time periods.

Interferences among passengers are considered in our simulation model, i.e., we implemented in the code a logic such that whenever a passenger stops in the aisle, the passengers behind him/her are forced to wait (unless available space exists between the stopping passenger and them). Likewise, similar logics have been implemented to account for interferences related to luggage handling or seat movements.

4.2. Aircraft and Load Factor

We represent the aircraft with a grid (see Figure 2 for an example). Each highlighted cell in the grid represents a seat. The load factor of a flight represents the percentage of seats occupied by passengers. This parameter is important because the more passengers, the more interference will exist and, therefore, it will take longer to complete the boarding.

We consider two levels of occupation, medium-high (load factor of 90%) and high (load factor of 100%). The level of passenger interference will be lower for lower load factors; therefore, we are not interested in studying low occupancy levels: the different boarding strategies will behave similarly.

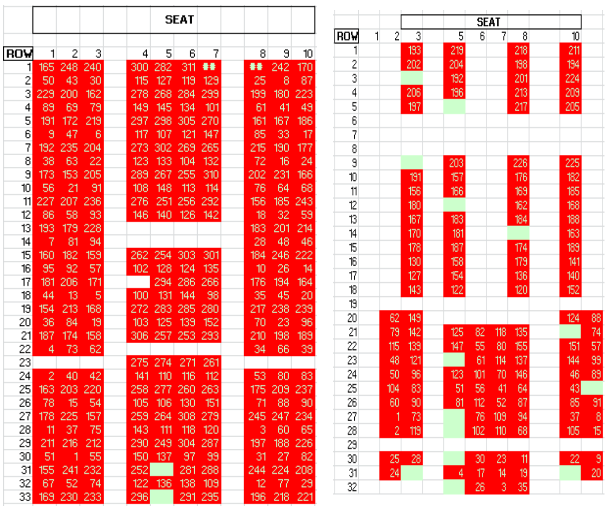

Figure 2: Aircraft grid for the simulation model: lower (left) and upper (right) decks.

5. COMPUTATIONAL RESULTS

Each aircraft type is classified according to the number of passengers that it can carry and the distance it can cover. The aircraft studied here is an Airbus 380-800 used by Singapore Airlines SQ with 471 seats on two decks: 12 Suite Class seats and 311 Economy Class seats on the main deck, and 60 Business seats and 88 Economy seats on the upper deck. There are three gates: two for the main deck (one for the Suite Class) and one for the upper deck of the aircraft.

We have developed an ad-hoc simulator using VBA inside Excel. With this software, we have performed simulations independently for the main deck and the upper deck. As we study 6 different boarding strategies and 2 different load factors, we carry out 12 simulations for the main deck and 12 for the upper deck; from each of the 12 simulations, 6 (one for each strategy) at a load factor of 90% and the other 6 at a load factor of 100%. We run 30 iterations for each simulation in order to have 30 different observations. The assignment of passengers to seats is randomly changed at each iteration. The Suite Class, which consists of 12 seats, has not been modelled since it has a self-boarding gate and is the area that requires the least boarding time.

The main objective is to observe the boarding time at the two decks. For each of the six strategies, the total boarding time will be the maximum time between the two decks.

5.1. Load Factor of 90%

In this subsection, we study the different boarding strategies for a load factor of 90%. We conduct the simulations independently for the main and upper decks.

5.1.1. Main deck

In order to be able to visually detect the differences between the six boarding strategies studied, we use a boxplot. Figure 3 shows a boxplot with the obtained results. The y-axis shows boarding times in time periods and the x-axis the strategy used (i.e., *Rand* for *random*, *BF* for *back-to-front*, *FB* for *front-to-back*, *ALTROW* for *alternating rows*, *BLOCKS* for *by blocks* and *RP* for *optimization*). The circle inside each box represents the average boarding time.

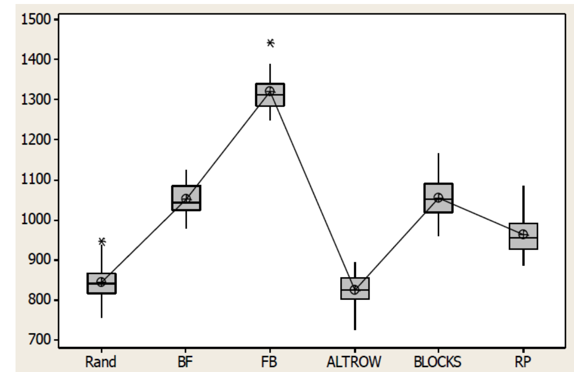

Figure 3: Boxplot for the main deck and load factor of 90%

Notice that there are two outliers, which are the extreme values of the data set (within the 30 observations, 2 have had a larger value than the average one). These values are represented by an asterisk in Figure 3. Regarding average values, the boarding times for *alternating rows* strategy appear to be the lowest, although the *random* strategy also provides low boarding times. The *front-to-back* strategy clearly provides the worst boarding times.

In order to examine whether there are significant differences between the average boarding times provided by the studied strategies we make an *Analysis of Variance (ANOVA).* Figure 4 shows the results. According to the p-value, which in this case is 0.000<0.005, we reject the null hypothesis: not all the (expected) boarding times are equal. The boarding times of *random* and *alternating rows* strategies and the *back-to-front* and *by blocks* are overlapping strategies: there are not many differences between them. For the other strategies there is no overlapping: the differences between them are significant.

We can conclude that the boarding strategy which works best on the main deck for a load factor of 90% is the *alternating rows* strategy.

```
Source   DF       SS      MS       F      P
Factor    5  4921282  984256  518,42  0,000
Error   174   330353    1899
Total   179  5251635

S = 43,57   R-Sq = 93,71%   R-Sq(adj) = 93,53%

Individual 95% CIs For Mean Based on
Pooled StDev
Level    N    Mean  StDev  ------+---------+---------+---------+---
Rand    30   843,6   44,6   (*)
BF      30  1051,7   35,2                 (*)
FB      30  1319,6   45,5                                  (*)
ALTROW  30   824,6   38,2  (*)
BLOCKS  30  1055,4   49,6                 (*)
RP      30   961,5   46,6          (*)
                           ------+---------+---------+---------+---
                               900      1050      1200      1350

Pooled StDev = 43,6
```

Figure 4: ANOVA for the main deck and load factor of 90%

5.1.2. Upper deck

The obtained results for the upper deck are similar to those ones for the main deck.

Figure 5 shows a boxplot so as to see the differences between the six boarding strategies studied. Figure 5 can be read the same way as Figure 3.

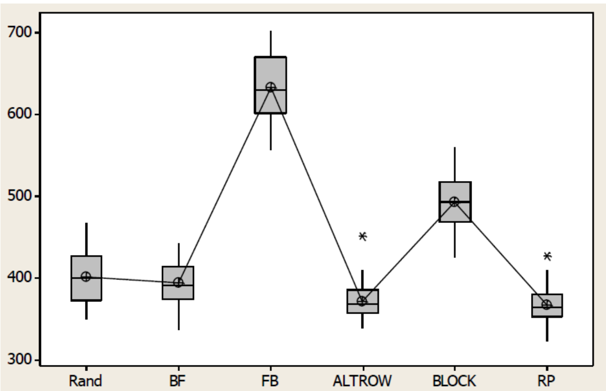

Figure 5: Boxplot for the upper deck and load factor of 90%

Again, there are two outliers, which are represented by asterisks. Regarding average boarding time values, *alternating rows* and *optimization* strategies provide the lowest ones. The *random* strategy also yields a low average boarding time. The *front-to-back* strategy is clearly the worst one; moreover the box is considerably wider as compared with the ones for the rest of the strategies.

Figure 6 shows the *ANOVA* results for the upper deck. According to the p-value, which equals to 0.000<0.005, we reject again the null hypothesis (homogeneity of expected boarding times). The average boarding times provided by the *random* and *back-to-front* strategies and, the *alternating rows* and *optimization* strategies overlap, which means that there are not significant differences between them.

Having a load factor of 90%, the *optimization* strategy is the one which works best on the upper deck.

```
Source   DF       SS      MS       F      P
Factor    5  1610375  322075  356,62  0,000
Error   174   157144     903
Total   179  1767519

S = 30,05   R-Sq = 91,11%   R-Sq(adj) = 90,85%

                                 Individual 95% CIs For Mean Based on
                                 Pooled StDev
Level    N    Mean  StDev  ----+---------+---------+---------+----
Rand    30  400,47  31,44     (*)
BF      30  393,73  25,29     (*-)
FB      30  632,97  38,28                                 (*)
ALTROW  30  371,53  23,91  (*-)
BLOCK   30  492,57  34,58                    (-*)
RP      30  366,90  23,62  (*)
                           ----+---------+---------+---------+----
                             400       480       560       640

Pooled StDev = 30,05
```

Figure 6: ANOVA for the upper deck and load factor of 90%

5.2. Load Factor of 100%

In this subsection, we study the different boarding strategies for the main and upper decks for a load factor of 100%. The obtained results are very similar to those ones for a load factor of 90%.

5.2.1. Main deck

Figure 7 shows the *ANOVA* results. The differences between the different strategies are statistically significant: the boarding time intervals of the strategies are separated from each other. We note that not all the boarding strategies produce the same boarding times (the p-value is 0.000).

The *alternating rows* strategy average boarding time is the lowest one, while the strategy *front-to-back* yields the greatest average boarding time. Therefore, the results are the same as those ones for a load factor of 90%.

```
Source   DF       SS       MS       F      P
Factor    5  6011086  1202217  731,62  0,000
Error   174   285920     1643
Total   179  6297006

S = 40,54   R-Sq = 95,46%   R-Sq(adj) = 95,33%

                                 Individual 95% CIs For Mean Based on
                                 Pooled StDev
Level    N    Mean  StDev  --+---------+---------+---------+--------
Rand    30   928,0   36,7     (*)
BF      30  1201,6   40,9                      (*)
FB      30  1444,0   51,1                                      (*)
ALTROW  30   905,8   34,6   (*)
BLOCK   30  1193,5   41,3                      (*)
RP      30  1089,7   36,4              (*)
                           --+---------+---------+---------+--------
                           900      1050      1200      1350

Pooled StDev = 40,5
```

Figure 7: ANOVA for the main deck and load factor of 100%

5.2.2. Upper deck

Figure 8 shows the boxplot for the upper deck and for a load factor of 100%. We note that there are no outliers. The best boarding strategy is the *alternating rows* one; moreover, its boarding times vary within a small range (see its box narrowness). The *front-to-back* strategy is the worst one.

The *ANOVA* analysis (Figure 9) shows the differences between the boarding strategies regarding boarding times. According to the p-value (0.000), the expected boarding times are not equal among the strategies. According to our experimental results, the *alternating rows* strategy is the most efficient one.

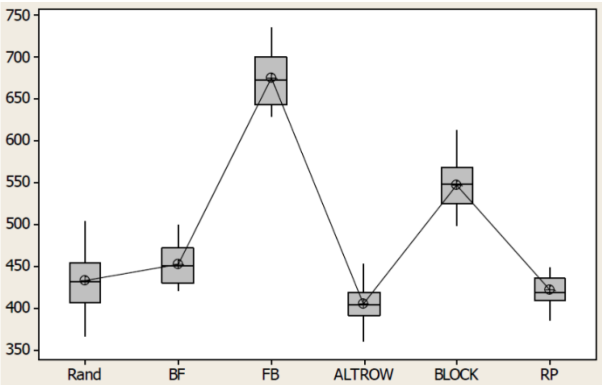

Figure 8: Boxplot for the upper deck and load factor of 100%

```
Source   DF       SS      MS       F      P
Factor    5  1624641  324928  476,61  0,000
Error   174   118625     682
Total   179  1743266

S = 26,11   R-Sq = 93,20%   R-Sq(adj) = 93,00%

                              Individual 95% CIs For Mean Based on
                              Pooled StDev
Level    N    Mean  StDev  --+---------+---------+---------+--------
Rand    30  432,60  32,94        (*)
BF      30  452,80  22,85          (-*)
FB      30  675,07  32,10                                    (*-)
ALTROW  30  404,90  21,73   (-*)
BLOCK   30  548,00  26,52                    (-*)
RP      30  422,00  16,65       (*)
                           --+---------+---------+---------+--------
                            400       480       560       640

Pooled StDev = 26,11
```

Figure 9: ANOVA for the upper deck and load factor of 100%

5.3. Summary of the Computational Results

The *alternating rows* boarding strategy is the most efficient strategy for both load factors of 90% and 100%. For a load factor of 90%, the *optimization* strategy works better in the upper deck; however, it provides little significant difference as compared to the *alternating rows* boarding strategy.

The computational results show that it takes more than twice the boarding time for the upper deck to board the main deck. This is due to the distribution of the seats in the upper deck: it provides less interference between passengers; moreover, the total number of seats is much lower in the upper deck than in the main deck.

Figure 10 shows boarding times for load factors of 90% and 100%. The total boarding time is significantly lower for the case where the load factor is 90%.

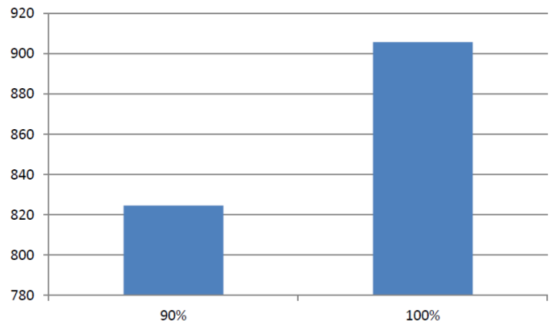

Figure 10: Boarding times for load factors of 90% and 100%

6. CONCLUSIONS

Conducting an efficient boarding process is a key step in order to minimize the total turn-time of an aircraft in an airport. We have demonstrated that different boarding strategies produce significant different boarding times.

One of the most important factors affecting the boarding times is the interference between passengers. Obviously, it depends on the number of seats and its distribution over the deck.

We show how for high load factor flights, small variations on it (i.e., within the range of 90-100%) do not have significant impacts on the boarding times and on the choice of the best boarding strategy.

The *back-to-front* boarding strategy, which is the traditional and most common strategy used by airlines (Herbst, 2007), is not the most efficient one for the aircraft studied in this paper: we have demonstrated that the one which works best is the *alternating rows* strategy. We acknowledge that this strategy may be confusing for the passengers. However, these negative effects may be alleviated if passengers are properly split into different passenger groups according to the strategy.

ACKNOWLEDGMENTS

This work has been partially supported by the Spanish Ministry of Science and Innovation (TRA2010-21644-C03) and by the Ibero-American Programme for Science, Technology and Development (CYTED2010-511RT0419), in the context of the IN3-HAROSA Network (http://dpcs.uoc.edu). Similarly, we appreciate the financial support of the Sustainable TransMET Network funded by the Government of Navarre (Spain) inside the Jeronimo de Ayanz programme.

REFERENCES

Bazargan, M., 2007. A linear programming approach for aircraft boarding strategy. *European Journal of Operational Research*, 183(1), 394-411.

Ferrari, P., 2005. Improving passenger boarding in airplanes using computer simulations. *International Airport Review*.

Ferrari, P., Nagel, K., 2004. Robustness of Efficient Passenger Boarding in Airplanes. *Transportation*

Research Board Annual Meeting'05, Preprint Number 05-0405.

Herbst, E., 2007. A tale of two aisles, *Control #2158*. http://homes.cs.washington.edu/~eherbst/projects/boom07/mcm07/report.pdf

Lewis, C., Lieber, R., 2005. Testing the latest boarding procedures; Airlines try new strategies to load passengers faster; The new meaning of groups. *Wall Street Journal*, New York, NY, 2 November 2005.

Marelli, S., G. Mattocks, R. Merry. 1998. The role of computer simulation in reducing airplane turn time. *Boeing Aero Magazine*, Issue 1.

Mas, Silvia. 2012. Aircraft Boarding Strategies: A study of the airline boarding problem. *B.Sc. Thesis*.

Nyquist, D., McFadden, K., 2008. A study of the airline boarding problem. *Journal of Air Transport Management*, 14(4), 197-204.

Steffen, J., 2008. Optimal boarding method for airline passengers. *Journal Air Transport Management*, 14(3), 146-150.

Steiner, A., Philipp, M., 2009. Speeding up the airplane boarding process by using pre-boarding areas. *9th Swiss Transport Research Conference.*

Van den Briel, M., Villalobos, J., Hogg, G., 2003. The aircraft boarding problem. *Proc. of the 12th Industrial Eng. Res. Conf.*, IERC, CD-ROM, article number 2153.

Van de Briel, M.H.L., Villalobos, J.R., Hogg, G.L., Lindemann, T., Mule, A.V., 2005. America West Airlines develops efficient boarding strategies. *Interfaces*, 35, 191–201.

Van Landeghem, H., Beuselinck, A., 2002. Reducing passenger boarding times in airplanes: A simulation based approach. *European Journal of Operational Research*, 142, 294–308.

AUTHORS BIOGRAPHY

LUIS CADARSO received the B.Sc., M.Sc. and Ph.D. degrees in aerospace engineering from the Technical University of Madrid, Spain. In September 2013, he joined the Department of Signal Theory and Communications, Faculty of Telecommunications, Rey Juan Carlos University, Spain, as a visiting professor. His research interests include operations research and its application to transportation.

NURIA PERELLÓ is a MSc student at the Autonomous University of Barcelona, where she got a Bachelor degree on Aeronautics Management. Her email is nuria.perello@gmail.com

ANGEL A. JUAN is an Associate Professor of Applied Optimization, Simulation, and Data Analysis in the Computer Science Department at the Open University of Catalonia (UOC). He is also a Researcher at the Internet Interdisciplinary Institute. He holds a Ph.D. in Applied Computational Mathematics, a MSc in Information Systems & Technology, and a MSc in Applied Mathematics. His research interests include Applied Optimization and Simulation. Currently, he is the coordinator of the CYTED-IN3-HAROSA@IB Network and editorial board member of both the Int. J. of Data Analysis Techniques and Strategies and the Int. J. of Information Systems & Social Change. He is also a member of the INFORMS society. His website is: http://ajuanp.wordpress.com.

JAVIER FAULIN is a Professor of Operations Research and Statistics at the Public University of Navarre (Pamplona, Spain). He holds a PhD in Economics, a MS in Operations Management, Logistics and Transportation and a MS in Applied Mathematics. His research interests include logistics, vehicle routing problems and simulation modeling and analysis. He is a member of INFORMS and EURO societies and an editorial board member of the International Journal of Applied Management Science and the International Journal of Operational Research and Information Systems.