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AGENT-BASED SIMULATION OF AIRCRAFT BOARDING STRATEGIES CONSIDERING ELDERLY PASSENGERS

Bruna H. P. Fabrin
Denise Beatriz Ferrari

Department of Management and Decision Sciences
Instituto Tecnológico de Aeronáutica
Praça Marechal Eduardo Gomes, 50
Vila das Acácias, 12228-900
São José dos Campos/SP, BRAZIL

ABSTRACT

Boarding is an important process for airline companies, with direct impact in operation efficiency and customer satisfaction. In some countries, priority boarding is required by law; elders, pregnant women, people with infants or disabilities have the right to embark first, regardless of ticket class, loyalty program or boarding group. The present work examines the effect of the adoption of priority boarding policy on total boarding time, along with other factors that are known to affect the efficiency of the boarding process, using an agent-based simulation model that represent the boarding process in a Boeing 767-300 aircraft. The simulated results indicate that the boarding process is improved by adopting priority boarding, which is beneficial not only to operational efficiency, but also has the potential of enhancing customer experience, thus suggesting that priority boarding should be a highly encouraged practice among airline companies.

1 INTRODUCTION

Before the COVID-19 pandemic imposed severe constraints on mobility of people around the globe and consequent unheard drop in transport activity was observed, data reports from 2019 show that approximately 46.8 million flights occurred in that year, involving roughly 4.5 billion passengers, with annual demand growth of about 4.2% worldwide (IATA 2019); these figures reveal the importance and reach of air transportation for global economic activity. The increase in demand for air transportation and the intensification of air traffic and congestion is expected to cause delays, leading to customer dissatisfaction and elevated costs to airline companies; each minute of delay has estimated cost varying from US$30 to US$250 (Horstmeier and de Haan 2001; Nyquist and McFadden 2008). An important performance indicator for determining profitability and competitiveness of airline companies is the so-called turnaround time (More and Sharma 2014): it consists of the time the aircraft remains on ground after its arrival at the gate, until it is ready for the next departure. Several operations take place during this interim, including airplane cleaning and fueling, disembarking and boarding of crew and passengers, complete unloading and loading of luggage and cargo, re-catering, among others. The boarding process has a major impact in turnaround time, thus optmizing this operation is critical (Neumann 2019). In fact, modifications implemented in the boarding process of an airline company in the past have proven to lead to a reduction of about 20% in boarding time (Briel et al. 2005).

Several factors are known to influence the boarding process, including number of passengers, aircraft capacity, and amount of carry-on luggage (Hutter et al. 2019). Passenger behavior is an important and somewhat unpredictable component; for instance, frequent flyers are more likely to be familiar with the process, and may help expedite it, while for someone who rarely flies, the boarding process can be confusing, which may contribute for additional delays. Previous research considered various factors that influence the boarding process and, consequently, should be addressed regarding its optimization, including possible interferences in the process (van den Briel et al. 2003; Steffen 2008; Delcea et al. 2018), the number of passengers (Schultz et al. 2013; Miura and Nishinari 2017) or passenger's group behavior (Cimler et al. 2012; Budesca et al. 2014; Iyigunlu et al. 2014; Zeineddine 2017), the quantity of luggage on-board (Milne and Kelly 2014; Notomista et al. 2016; Tang et al. 2018), as well as combinations of such human factors. Likewise, new concepts for cabin configuration that may promote a smoother boarding operation have been investigated (Schmidt et al. 2016).

The boarding strategy is also expected to influence the boarding process. Some studies suggest that random boarding is faster than the back-to-front strategy: Van Landeghem and Beuselinck (2002) used simulation and considered several boarding strategies; Ferrari and Nagel (2005) adopted a deterministic process; and Qiang et al. (2017) carried out an experimental test in a school bus. In contrast, other authors concluded that back-to-front is a better boarding strategy: Schultz et al. (2013) conducted an assymetric simple exclusion process and considered different airplanes (A320-200, B777-200 and A380); Delcea et al. (2018) used agent-based simulation and several luggage scenarios.

In most countries, passengers who wish to board first due to any special reason may do so by requesting for assistance prior to regular boarding. However, this process is not mandatory and requests are dealt with as best suited for airline companies. In Brazil, in contrast, according to Resolution nº 280 from July 11th, 2013, issued by the Brazilian Civil Aviation Regulatory Agency (ANAC), elderly passengers (above 60 years), pregnant women, passengers with infants, or with disabilities have priority boarding.

Thus, the present work contributes to the subject by evaluating the effect of priority boarding of passengers with special needs combined with different boarding strategies on boarding time. This is achieved by modeling a heterogeneous population, i.e., to each passenger is randomly apppointed an age group, a walking speed and a time to allocate the luggage in the overhead bin. In order to do so, an agent-based simulation model has been proposed. The use of computer simulations offers the benefits of (i) low cost, (ii) safety, as well as the (iii) possibility of representing various scenarios. An agent-based simulation approach allows the modeling of a heterogeneous population whose behavior evolves with time and according to interactions with other agents (Bonabeau 2002).

2 METHODOLOGY

An agent-based model (ABM) was adopted for boarding simulation. In the ABM approach, the system is comprised of a set of independent entities (called agents) that may interact with one another. As each agent has its own characteristics and makes its own decisions based on a given set of rules, ABM is able to capture the random nature associated to the aircraft boarding process, regarding both the environment conditions (airplane structure) and the passengers' (physical, behavioral) characteristics. The simulation model was implemented in the open agent-based modeling environment NetLogo (Wilensky 1999) to simulate various boarding scenarios. In all of the following discussions the characteristics of a Boeing 767-300 aircraft will be used as an example. The process is general, though, and can be applied to any aircraft configuration.

The cabin layout is based on a Boeing 767-300 aircraft, with seat configuration 2-3-2, and maximum capacity of 294 passengers. The twin aisle aircraft accommodates a total of 42 rows and 8 exits. The cabin is discretized into 0.5 m x 0.5 m nodes, classified as structures (seats, toilet, and fuselage) or open spaces (aisles, legroom and exits), as illustrated in Figure 1. The simulation time is set so that 20 ticks correspond to 1 second.

The most common boarding strategies are considered: (i) random, (ii) back-to-front by-blocks, (iii) luggage-first, and (iv) two-doors. Different boarding scenarios are evaluated regarding a probability factor of passengers having carry-on luggage; the examined possibilities are: (i) 10%, (ii) 50%, (iii) 75%, and (iv) 100%. Likewise, three load factors are considered: (i) 147, (ii) 235, and (iii) 294 passengers. Elder passengers are modeled as heterogeneous agents with different characteristics, and the combination of the above-mentioned factors in scenarios with and without priority boarding are evaluated.

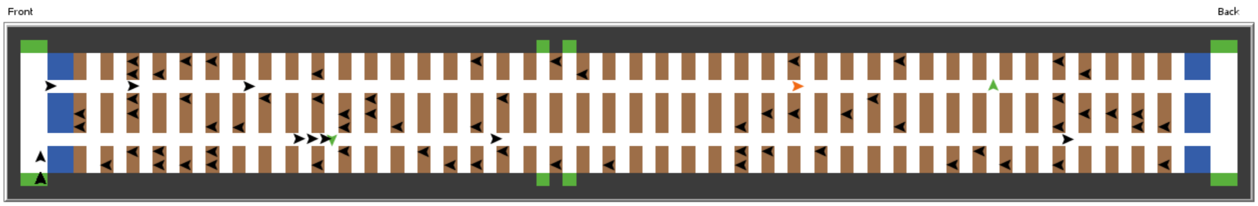

Figure 1: Example of boarding simulation for the Boeing 767-300 aircraft. Arrows correspond to passengers and their facing directions; white cells represent open spaces where passengers can walk freely, such as aisles and legroom; brown cells represent seats; blue cells represent aircraft internal structures; and green cells represent doors and emergency exits.

2.1 Passenger's Characteristics

There are four characteristics that differentiate passengers from each other: (i) age and, consequently, walking speed; (ii) seat ticket assignment; (iii) possession of carry-on luggage; and (iv) time needed to store luggage at overhead bin.

In this study, priority boarding is assigned to a passenger according only to his or her age. Thus, the model incorporates different age groups, following the Brazilian population distribution from 15 to 74 years of age (IBGE 2010): (i) 15-16, (ii) 17-25, (iii) 26-50, (iv) 51-64, and (v) 65-75 years; for each age group, a particular walking speed is defined as follows.

Most of the studies addressing walking dynamics are set in open spaces, characterized by free flow of people. In the literature (Willis et al. 2004), pedestrians are observed on a street, and their walking speeds, which depend on their ages, are modeled as a random variable with normal distribution with mean of 1.47 m/s and standard deviation of 0.299 m/s. A previous study (Mas et al. 2013), based on empirical observation of a real life aircraft boarding process, determined a mean walking speed of 0.5 m/s, when all passengers are considered equally. In order to model different walking speeds for agents within the aircraft cabin, the strategy adopted in the present investigation consists in applying for each age interval a correction of the reference speed value (0.5 m/s) according to free flow walking speed distribution.

Seat tickets are randomly distributed among passengers, and all seats inside the airplane are available. Moreover, all passengers are assumed to be traveling alone, i.e., there is no group formation. Therefore, passengers enter the cabin one at a time, with a destination seat, since there is no free or preferred seating.

Each passenger is allowed to have at most one carry-on luggage and there is no physical limitation to the overhead bin. The possession of a carry-on luggage is determined randomly, according to an assigned probability: when this probability is set to 0, no passenger carries a piece of luggage on-board; if the probability is set to 100%, every passenger has a carry-on luggage. Four different values for this probability are evaluated, as described above.

Lastly, aisle interference is created by assigning to each passenger a time needed to store the luggage at the overhead bin. This storing time is modelled as a random variable that follows a Weibull distribution, defined from field trial measurements (Schultz 2018). This distribution is independent of the passenger's age. In the present simulation study, if an agent is flagged as an elder, his or her luggage storing time is increased in 20%.

2.2 Scenarios Setup

The different simulated scenarios are determined by the combinations of levels of the following factors: (i) priority boarding setting (PRI), (ii) number of passengers onboard (PAX), (iii) passenger's luggage possession probability (LUG), and (iv) boarding strategy (STR). The levels for each factors are presented in Table 1.

Priority boarding (PRI) can be set either to (i) "on" or (ii) "off". If it is set "on", all agents flagged as elders enter first, regardless of the boarding strategy. After that entire group has boarded, the rest of the

Table 1: Factors and corresponding levels used to create different simulation scenarios.

Factor	PRI	PAX	LUG	STR
Levels	On	294 pax	10%	Random
	Off	235 pax	50%	Back-to-front by block
		147 pax	75%	Luggage-first
			100%	Two-doors

agents may enter, according to the determined boarding strategy. It means that, after priority boarding occurs and other passengers start to enter, some of the seats are already taken, probably causing interferences. The simulation model does not admit the occurrence of late comers.

The aircraft load factor can take the values: (i) 147 (50%), (ii) 235 (80%), or (iii) 294 (100% airplane capacity) passengers. The possession of luggage depends on the probability that may assume values: (i) 10%, (ii) 50%, (iii) 75% and (iv) 100%. In this study, it is assumed that there is no physical limit onboard to the quantity of carry-on items, i.e., the overhead bins can hold as much luggage as needed.

Regarding boarding strategy, the passengers can come aboard: randomly; from back-to-front, organized by blocks; or those carrying luggage enter first; or, still, they can get into the plane using one of two doors. As stated before, within its designated group, the order in which passengers enter the cabin is always random. When simulating random boarding strategy, no order is defined, and passengers come onboard according to a first-come first-serve (FCFS) fashion. In back-to-front by-blocks strategy, three boarding groups with equal number of passengers are defined (front group, middle group, and back-group); the first passengers to get into the cabin are those in the back group, followed by those in the middle group and, finally, those in the front group. Another boarding strategy consists in allowing that all passengers carrying a luggage enter first in random order, and then passengers without luggage are allowed to come aboard. Lastly, when two doors are available, passengers are allowed to board the aircraft simultaneously from either the front or rear door, assuming they know exactly which door they should use. Agents are equally divided in two groups, so that passengers seating in the front half of the airplane enter through the front door, and passengers seating in the rear half enter through the back door. If two doors are used with priority boarding, elderly passengers are assumed to enter first through both doors at the same time. This is a simplification, because airports don't usually dispose of two jetways per gate and this strategy would only be available when using buses. If that is the case, when buses are fully loaded, priority boarding is difficult to follow due to passenger's hurry to enter the cabin. Yet, in reality, loading through buses may still also not happen simultaneously, as it is unlikely that the buses arrive at the apron position at the same time.

2.3 Other Simulation Parameters

There are two additional simulation parameters which are fixed values and cannot be controlled from the simulation interface: (i) passenger flow rate, and (ii) seat shuffle time.

Passenger flow rate is the time gap between successive passengers entering the aircraft. The value of this rate depends on the gate control, which is the point where the airline company employees check the passenger's identification and travel ticket. The literature reports values varying from 9 pax/min (Marelli et al. 1998) or 14.1 pax/min (Schultz 2017) to 20 pax/min (Boeing 2005). It is understood that this rate, in real situations, varies throughout the boarding process, and may be modeled as a random variable: at the beginning of the boarding process, a higher flow may be observed, and as more passengers are already inside the cabin, the rate decreases. In the present study, the fixed value of 14.1 pax/min is used, representing the situation in which passengers enter the cabin uniformly, one at a time, at constant that rate.

Seat shuffle time is the time needed for a seat interference to be resolved. For example, a passenger assigned to a window seat may be blocked by a passenger already accommodated at the aisle seat. It is possible to define different shuffle time values, depending on the interference situation underway (Schultz

2018). The simulation model assumes that all seat shuffles take 10 seconds, a time during which the passenger who wishes to seat, stays in the aisle blocking the other passengers that come in.

2.4 Simulation Process

The combination of all factors levels gives a total of 96 possible scenarios; for each one of them, 100 runs are made for statistical relevance, resulting in a total of 9600 simulation runs. In Figure 5, a simplified diagram representing the simulation process is shown.

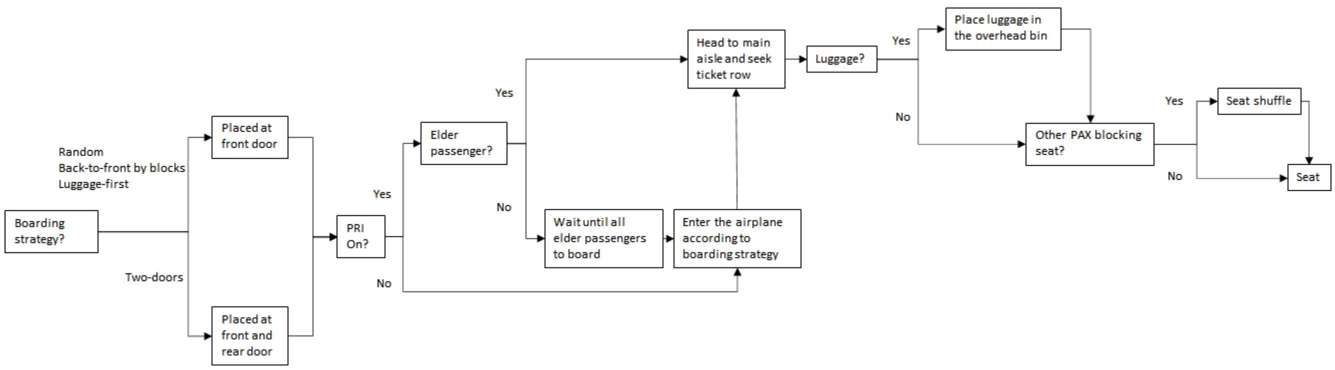

Figure 2: Simulation diagram, regarding order of steps and processes.

At the beginning of the simulation, all agents representing the passengers are created and wait at the assigned entering door for their turn to enter the cabin. Passengers are positioned by the left front door for random, back-to-front by-block, or luggage-first strategies; while for the two-doors strategy, the passengers are positioned before both left doors (front and rear). It is important to stress that passengers cannot walk past one another, i.e, if there is a slow moving passenger ahead, or if there is an aisle interference, passengers behind are not able to move freely and overtake the slow passenger. In those cases, they must wait until the former passenger sits, so then they be allowed to resume his or her normal speed.

With a seat ticket in hand, and assuming that there is a crew member assisting the passenger in identifying the assigned seat with no mistakes, he or she walks towards the assigned seat row. There are no lost individuals in the process. When the passenger reaches the destined position, if the passenger is carrying luggage, a time delay will be added, representing the time needed to store it in the bin. In this case, the delay will be determined according to the Weibull distribution, as previously described; for elderly passengers, the time needed to store luggage is increased in 20% on top of that. Then, he or she first checks if there is no seat interference, i.e., if there is no other agent seating at the same row and blocking his or her way. If that is the case, another time delay of 10s (seat shuffle time), will be added in order to represent the time needed to resolve the interference. During these time delays, a passenger will be in the aisle, blocking other passengers who need to proceed. After that passenger takes the seat, the previously blocked agents in the aisle resume their movement.

The simulation begins when the first passenger enters the airplane and it ends when all passengers are seated. At the end, the total boarding time is computed. Notice that some simplifying assumptions are made in the present model: passengers commit no mistakes in choosing the aisle or finding their seats; passengers do not surpass one another and wait until the path is free; and there is no physical limitation to the overhead bin, allowing all passengers to carry a bag onboard.

3 RESULTS AND DISCUSSION

The following results were obtained from 100 replicates of a full factorial experiment, consisting of 96 possible scenarios.

ANOVA is performed in order to evaluate the effects of the considered factors (PAX, PRI, STR, LUG) on the total boarding time. The results are displayed in Figure 3. For a 5% significance level, all factors and first-order interactions are significant, which means that they affect the total boarding time.

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Analysis of Variance Table

Response: TBT
            Df    Sum Sq   Mean Sq    F value    Pr(>F)
PAX          2 637693863 318846931 1.3822e+06 < 2.2e-16 ***
PRI          1   9648003   9648003 4.1825e+04 < 2.2e-16 ***
STR          3   3018529   1006176 4.3618e+03 < 2.2e-16 ***
LUG          3   1159934    386645 1.6761e+03 < 2.2e-16 ***
PAX:PRI      2     33831     16915 7.3329e+01 < 2.2e-16 ***
PAX:STR      6     33102      5517 2.3916e+01 < 2.2e-16 ***
PAX:LUG      6      7261      1210 5.2462e+00 2.096e-05 ***
PRI:STR      3    218594     72865 3.1587e+02 < 2.2e-16 ***
PRI:LUG      3    409612    136537 5.9190e+02 < 2.2e-16 ***
STR:LUG      9    240448     26716 1.1582e+02 < 2.2e-16 ***
Residuals 9561   2205513       231
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 3: ANOVA table.

A linear regression model for the main effects is fit to data and the estimated coefficients are displayed in Figure 4. The baseline levels for factors PAX, PRI, STR and LUG are, respectively: load factor of 100% (294 pax), priority off, random strategy, and luggage probability of 10%. It means that the estimates represent expected variations in response compared with the baseline values. The model is significant (F-statistic = 2.205e+05) and the adjusted-R squared (0.9952) indicates that most of data variability is explained by the calibrated model.

It is important to underline that these results are not expected to be interpreted as “true” values, in the sense that validation with real data was not performed. However, care was taken in building a realistic simulation model, and several tests have been conducted in order to verify whether the simulation model performs as designed, and that the simulation model is relevant. Therefore, these results are valuable for gaining insights in terms of relative comparisons, and reaching qualitative conclusions. Thus, for comparison purposes, simulated total boarding times averages and respective standard deviations are presented in Table 2. As it can be observed, the standard deviation of most factors are quite large. This is mainly due to the influence of the number of passengers, which affects the response significantly.

The results for the regression model (Figure 4) and the averages (Table 2) allow drawing interesting conclusions. Compared to the baseline value of 294 passengers, decreasing the load factor in 20% significantly decreases the total boarding time in 251 seconds (19.32%) on average. A similar effect is observed when load factor corresponds to 50% of total capacity: the total boarding time drops 627 seconds (48.25%) on average. Of course, these are expected results that relate to reality. Intuitively, whenever there are less passengers on board, the whole boarding process is expected to take less time. It is interesting to verify a linear effect of PAX factor on the response, which is in agreement to previous findings reported in the literature (Schultz 2017; Hutter, Jaehn, and Neumann 2019).

The main purpose of the present study was to evaluate the effect of priority boarding requirements on total boarding time. According to the simulated results, there is evidence that implementing the priority boarding of elderly passengers has a significant effect in abbreviating total boarding time, as seen in the

```
Residuals:
    Min      1Q  Median      3Q     Max
-58.756 -11.477  -0.988   9.982 141.268

Coefficients:
                  Estimate Std. Error  t value Pr(>|t|)
(Intercept)      1340.0348     0.5848  2291.49   <2e-16 ***
PAX147           -627.1875     0.4530 -1384.60   <2e-16 ***
PAX235           -251.1770     0.4530  -554.51   <2e-16 ***
PRIOn             -63.4035     0.3699  -171.43   <2e-16 ***
STRBack-to-front  -33.9082     0.5230   -64.83   <2e-16 ***
STRLuggage-first  -11.3117     0.5230   -21.63   <2e-16 ***
STRTwo-door       -44.7744     0.5230   -85.60   <2e-16 ***
LUG50               9.4346     0.5230    18.04   <2e-16 ***
LUG75              16.0330     0.5230    30.65   <2e-16 ***
LUG100             30.1975     0.5230    57.73   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 18.12 on 9590 degrees of freedom
Multiple R-squared:  0.9952,Adjusted R-squared:  0.9952
F-statistic: 2.205e+05 on 9 and 9590 DF,  p-value: < 2.2e-16
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Figure 4: Linear model coefficient estimates.

regression model and Table 2. Although this result may appear counterintuitive, it indicates that allowing elder passengers, who are likely to require more time to settle, may improve the boarding process both in terms of operation, since the total boarding time becomes 6% faster on average, as well as in terms of customer satisfaction, as reported in Erland et al. (2019).

From the simulation results, the boarding strategy adopted also exhibits a significant effect on total boarding time. Slower boarding is likely to happen when the random (baseline) strategy is adopted. Successive improvements in total boarding time are observed for other strategies in the following order: luggage-first (average 1% decrease), followed by back-to-front by-blocks (3.3% decrease on average) and, finally, two-doors (4.35% average improvement). In this study, back-to-front strategy seems to be a better solution than random boarding.

In the present study, the two-doors strategy has the largest effect on decreasing total mean boarding time. This strategy is implemented in the present simulation model as random boarding with double boarding rate, since passengers embark from two available doors simultaneously, in random order. Thus, it is possible that combining other strategies with two-door configuration may further improve the boarding process. In Delcea et al. (2018), Delcea et al. (2019), Milne et al. (2019), random boarding is compared to a back-to-front strategy and several other optimized methods applied to two-doors boarding, in a single aisle aircraft. In those studies, the alternative strategies are faster than random boarding, which strengthens the proposed argument.

Finally, as it is expected, increasing the amount of carry-on luggage onboard leads to statistically significant slower boarding processes. When all passengers have a piece of luggage, the highest impact in total boarding time is observed, corresponding to an increase of 30 seconds (2.95%) on average, compared to the situation in which only 10% of passengers possess a carry-on item. Intuitively, it is expected that the amount of luggage contribute to a sharp increase in total boarding time. Although the simulation results

Table 2: Simulated total boarding time averages and standard deviations.

Factor	Level	Average (s)	Std-Dev (s)
PAX	294 pax	1299.75	44.72
	235 pax	1048.57	42.66
	147 pax	672.56	38.56
PRI	Off	1038.66	261.84
	On	975.26	256.60
STR	Random	1029.46	262.48
	Back-to-front by-blocks	995.55	261.02
	Luggage-first	1018.15	261.51
	Two-doors	984.67	257.33
LUG	10%	993.05	259.09
	50%	1002.48	260.24
	75%	1009.08	260.41
	100%	1023.24	264.09

show that the effect of luggage in total boarding time is significant, it has not proven to be as strong as one might presume. It may be explained by the fact that in the simulation model the overhead bin presents no physical restrictions, which means that the effect of rearranging or finding space is not assessed. This could be an important source of delays.

Interaction plots are provided for assessing the effects of different combinations of factors levels. The interaction plots in Figures (5a)–(5c) lead to the conclusion that increasing the number of passengers tends to increase the total boarding time, whether there is priority boarding policy or not, and also irrespectively of boarding strategy or the amount of carry-on luggage. Although the ANOVA results indicate statistical significance of such interaction effects, these do not seem to have important practical significance.

The interaction plot in Figure (5d) indicates that when priority boarding is adopted, all boarding strategies show significant decrease in total boarding time, with the random boarding (both one or two-doors) strategies showing the greatest benefits. It indicates that any sort of rule or order is beneficial to the boarding process and, thus, such actions should be encouraged. On the other hand, the total boarding time is least affected by the combination of priority boarding with back-to-front by-blocks strategy, since this boarding strategy already has significant effect on total boarding time.

The interaction plot in Figure (5e) suggests that priority boarding tends to have a more significant decrease in total boarding time in situations in which more luggage are carried aboard. Also, when priority boarding is adopted, smaller differences in total boarding times are observed when the amount of luggage onboard varies; the boarding process efficiency seems to be more robust to change in quantity of bags when elderly passengers have priority on the embark.

Finally, Figure (5f) shows the interactions between STR and LUG. The percentage of luggage onboard increases the total expected boarding time regardless of the boarding strategy adopted, as expected. Nonetheless, the effect of this interaction is significant: random (one or two-doors) and back-to-front by-blocks strategies are affected similarly by the increase in the amount of carry-on luggage brought by passengers. When the passengers with carry-on luggage embark first, however, the total boarding time remains roughly the same if the percentage of luggage is less than 75%. A sharp increase in total boarding time is observed when the totality of passengers possess a piece of luggage; this makes perfect sense, since now this strategy is equivalent to random boarding.

4 CONCLUDING REMARKS

The main objective of the present study was to evaluate the effect of elderly priority boarding requirements on total boarding time, along with other factors that are known to affect the efficiency of the boarding process. In order to do so, an agent-based simulation model was built to represent the boarding process in a Boeing 767-300 aircraft; 100 replicates of a full-factorial experiment with four factors (load factor, priority boarding for elder passengers, boarding strategy and amount of carry-on luggage onboard), consisting of a total of 96 scenarios (equivalent of 9600 runs) were performed.

The simulated results showed that, as expected, as both the number of passengers and the amount of luggage onboard increase, the total mean boarding time also escalates. Moreover, the random boarding strategy proved to be the least efficient among the strategies investigated, while random embarking using two-doors led to the smallest expected total boarding time, closely followed by the back-to-front by-blocks boarding strategy. Therefore, it appears that establishing some structure and order to the boarding process contributes to its efficiency. There are important interactions among the priority boarding of elderly passengers, the boarding strategy and the amount of luggage onboard.

The simulated results indicated that the boarding process is improved by adopting priority boarding, i.e., when slower passengers or passengers who may need extra time to settle, such as elders or passengers with special needs, embark first. In all simulated scenarios, significant reduction in total boarding time is observed if priority boarding is adopted, when compared to the standard random boarding process. Another interesting finding is that process with priority boarding indicates a better robustness regarding the amount of luggage onboard, being less affected by it. Thus, not only the priority boarding policy benefits operational efficiency, but also it has the potencial of enhancing customer experience. This is probably the most valuable insight from the simulated results, and it suggests that this should be a highly encouraged practice among airline companies.

The proposed work was a preliminary study that can be easily generalized in order to include new features that confer more realism to the simulation. A possible future direction consists in comparing strategies in different airplane settings, such in narrow body single aisle aircraft. In our study, all passengers follow the airline instructions to boarding. However, in reality it is hardly true. For example, in future studies, passengers who arrive late may be implemented so that their impact in the process may be analyzed. Another possibility is to allow the detours of passengers so that they be able to surpass a blocking passenger. Also, future endeavors should include modeling overhead bin capacity, so that if it gets full, passengers would have to find alternative space to storage their luggage.

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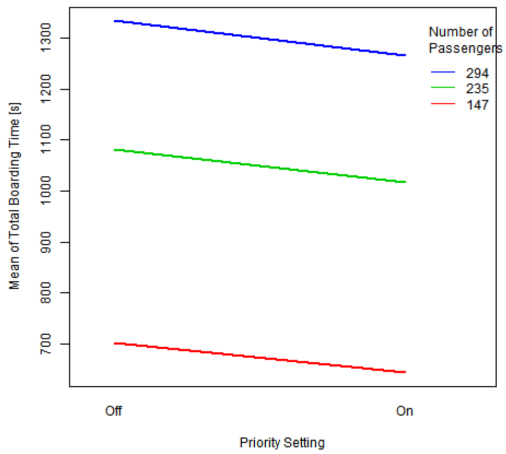
AUTHOR BIOGRAPHIES

BRUNA H. P. FABRIN is a doctorate student of Operations Research in the Department of Management and Decision Sciences at Instituto Tecnológico de Aeronáutica. She received her B.S. in Mechanical Engineering from Universidade Estadual de Campinas. Her email address is bfabrin@gmail.com.

DENISE BEATRIZ FERRARI is an assistant professor at the Department of Management and Decision Sciences at Instituto Tecnológico de Aeronáutica. She received M.S. and Ph.D. degrees in Statistics from University of California Los Angeles, as well as a M.S. degree in Aeronautical and Mechanical Engineering and B.S. in Mechanical-Aeronautical Engineering from Instituto Tecnológico de Aeronáutica. Her research interests include quantitative methods for decision making, statistical modeling and data analysis, and simulation-based optimization, applied to product development and operations in aeronautics. Her email address is denise@ita.br.



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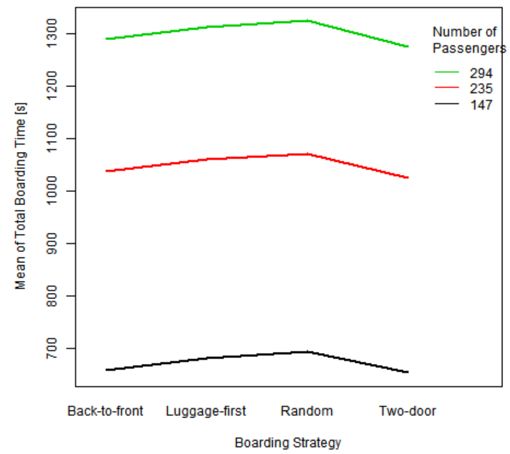

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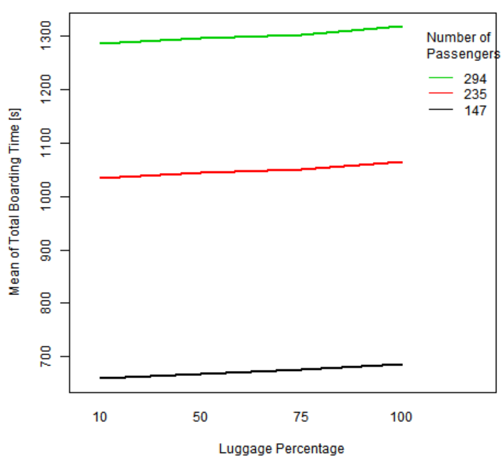

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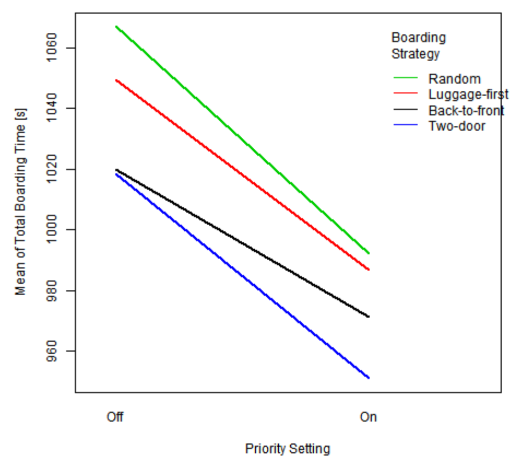

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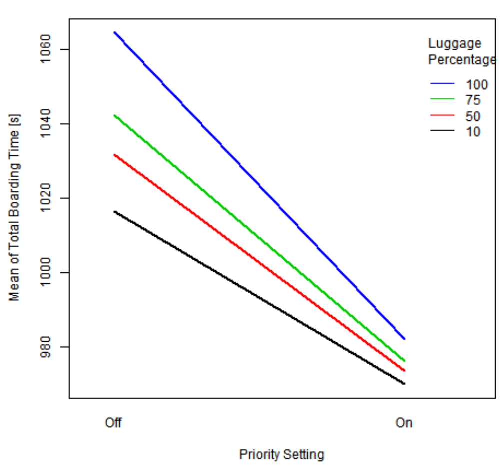

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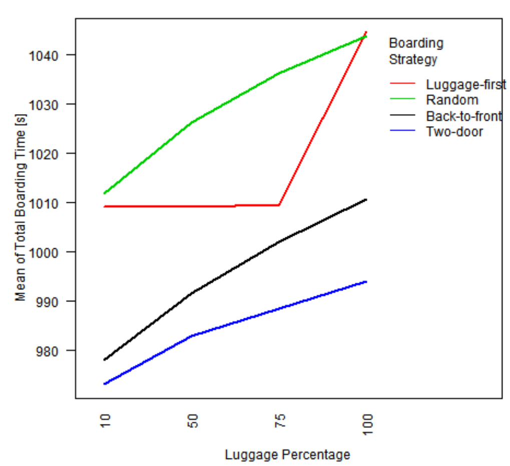

(f) STR and LUG.

Figure 5: Interaction plots.