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Article

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Towards balancing efficiency and customer satisfaction in airplane boarding: An agent-based approach

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ABSTRACT

The airplane boarding process, which can have a significant impact on a flight's turnaround time, is often viewed by researchers and airlines primarily in terms of minimizing total boarding time (TBT). Airplane capacity, number of passengers on board, amount of luggage, and boarding strategy are common factors that affect TBT. However, besides operational efficiency, airlines are also concerned with customer satisfaction, which affects customer loyalty and financial return. One factor that influences passenger experience is the individual boarding time (IBT), here defined by the time passengers stand inside the cabin. Considering these two aspects, an agent-based model is presented that compares the performance of three alternative mainstream boarding strategies in a 132-seat and a 160-seat single-aisle commercial airplane. An important characteristic of the model that differentiates it from previous work is that overhead bins have a physical limitation, which could lead to an increase in aisle interferences on full flights as passengers take longer to find a place for their carry-on luggage. Another important contribution is the analysis of how passenger seat location affects IBT. Our results show that outside-in (OI) produces shorter TBT than random and back-to-front boarding, and also shorter IBT and much shorter maximum IBT than BTF, particularly for passengers seated in the middle of the airplane. This suggests that among the three most popular boarding strategies used by airlines across the world, OI is the best when it comes to balancing airplane boarding efficiency with individual customer satisfaction.

1. Introduction

In 2022, airlines revenue reached US\$ 727 billion, representing 87% of pre-pandemic levels [1]. As the industry continues its recovery, the aviation market is expected to grow annually by 3.3% and reach nearly 8 billion passenger trips per year by 2040 [2]. With this anticipated market growth, airport operations are expected to encounter more infrastructure challenges, such as traffic control or airport capacity constraints. Many airports around the world already face regular delays and crowding, primarily caused by air carrier delays, airplane late arrivals, and reactionary delays [3–5]. These delays not only contribute to airport congestion but also increase the workload of air traffic controllers [6]. As a result, airlines are under increasing pressure not only to improve operational efficiency, but also to maintain or enhance current levels of customer satisfaction. From the passenger's perspective, overcrowding and delays are perceived as signs of poor service quality, which may lead to negative feedback and influence the airline choice [7].

A key performance indicator used by airlines that is closely tied to revenue and customer satisfaction is the turnaround time. Turnaround time is defined as the time interval between the arrival of an airplane and its departure from the gate. During this time, several operations are performed, such as fueling, catering, boarding and deboarding of passengers and crew, as well as the airplane maintenance [8]. Since airline companies generate revenue only while flying, the shorter the turnaround time, the more revenue the airlines should be able to generate. Moreover, airlines must adhere to schedules set by air traffic control and the airport. It is estimated that each minute on the ground costs the airline between US\$ 30 and US\$ 250, depending on the type of airplane [9,10].

Boarding is a crucial activity that takes place during the turnaround time because it is one of the lengthiest procedures [11] and falls on the critical path of the turnaround [12], which means that a delay in boarding usually leads to a delay in the whole process. Additionally, boarding is highly variable, since it is very much influenced by

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the human factors involved. It significantly affects passengers' experiences [13], which in turn influences their perception of the airline's service quality [14]. Consequently, it is a key determinant of customer satisfaction or dissatisfaction [15].

The boarding process consists of passengers entering the airplane one at a time. They may or may not have luggage. Upon entering, the passenger proceeds to their assigned row, stores their luggage (if applicable) in the overhead bin, and then takes their assigned seat. In the process, the passenger may need to wait while others stand in the aisle to store luggage or resolve a seat interference. Seat interference occurs when a passenger cannot take their window or middle seat immediately because another passenger already seated in the same row (in the middle or aisle seat) must get up first [16]. Due to limited storage capacity, nearby overhead bins may be full by the time a passenger arrives at their assigned seat. As a result, they may have to move around to find an available space to stow their carry-on bag.

Key factors that affect the airplane boarding process include the number of passengers on board, the airplane model (cabin layout), the type of flight (business or leisure), the presence of groups or families traveling together, the number of carry-on items on board, as well as passenger's characteristics [17–22]. Variations in these factors can have a significant impact on total boarding time [23], which is considered the most critical measure of an airline's boarding success. While infrastructure changes or the introduction of new technology – often expensive and time-consuming – are options for reducing total boarding time, a more immediate solution is to adopt more efficient boarding strategies.

To date, the scientific literature on airplane boarding has focused primarily on reducing total boarding time by evaluating alternative boarding strategies. Several strategies have been proposed [17,24–29] that take into account factors such as passenger diversity [19,20,30,31], amount of luggage on board [32–36], groups traveling together [17, 26,33,35,37], and COVID-19-related social distancing [38,39]. The methodologies used in these studies have been diverse, including integer programming [36,40–42], pedestrian dynamics [43], discrete event simulation [44,45], machine learning [46], experimentation [47,48], physics and optics [31,49], cellular automata [50,51], and agent-based modeling [28,52–54].

Results so far have shown that no strategy is universally the most effective in terms of total boarding time across all possible boarding scenarios, although group boarding has consistently been shown to be slower than others [28,44,53,55,56], while some authors emphasize that random boarding performs poorly [57,58]. From an airline perspective, outside-in boarding is generally considered the most efficient strategy due to fewer interference events [55,57,58], despite being considered a group boarding strategy. As previously mentioned, fewer studies have focused on individual passenger metrics. Nevertheless, these studies have indicated that back-to-front boarding results in the longest individual boarding times (IBT) [20,28,44].

In practice, when an airline is selecting a boarding strategy to adopt, it must consider not only operational efficiency but also customer satisfaction. This aspect has so far received little attention from the scientific literature. A recent online survey of 1500 passengers found that while passengers value fast overall boarding times, getting to their seats quickly is even more important to them [59]. The modeling studies so far which considered individual passenger interest have indicated that back-to-front boarding strategy is the worst option because it results in the longest individual boarding times [20,28,44].

The present work proposes a spatially-explicit agent-based model (ABM) to compare the performance in a commercial airplane of alternative boarding strategies with respect to balancing airline revenue with customer satisfaction. Here three main-stream boarding strategies are compared: outside-in, back-to-front and random. The model represents single-aisle airplanes, like the B737 or A320, which may accommodate varying passenger capacities. Such airplanes are typically utilized for short- and medium-haul flights, in which boarding time is particularly

critical compared to long-haul flights [16]. Here, the airline's interest is assessed via measurements of the total boarding time (TBT), defined as the time interval from the first passenger entering the airplane to the last passenger sitting. Passenger preference for faster seating is assessed with two measures: individual boarding time (IBT), here defined as the time interval between a passenger entering the airplane and sitting, i.e., the total time walking or standing inside the airplane, and the maximum individual boarding time (MAXIBT) per boarding process. MAXIBT was included to allow for the assessment of the disproportionately large negative effect on an airline that a few extremely dissatisfied customers might impose, in terms for example of judicial problems or negative social media campaigning.

In a real flight situation, the passenger demographics may change depending on the route. For example, air shuttle flights are typically flown by individuals who travel frequently and alone, and are therefore familiar with the boarding procedure. In contrast, tourist flights are largely made up of families or elderly passengers who may take longer to sit down. This study does not consider any particular type of flight and assumes that individuals travel alone, carrying or not a standardized piece of luggage. Based on input from airline executives and information obtained from Boeing's website [60], the overhead bins in the present simulation are modeled with limited capacity. In other words, there is insufficient space for every passenger to bring and store a piece of luggage on board. To the best of our knowledge, this aspect has not been addressed in scientific literature before. The usual approach involves increasing storage time in order to account for the number of bags passengers carry [18,33,44,61,62]. This makes the proposed model more realistic, as limited storage space may force some passengers to stow their luggage farther from their seats, causing aisle congestion.

The main contribution of this work lies in the development and analysis of an agent-based model that differs from previous models in that it takes into account the physical limitation of overhead bins, and enables the comparison of the performance of alternative boarding strategies in terms of measures that reflect the interests of both airlines and passengers. In addition, this study examines how passenger seat locations affect individual boarding times, which is an important factor in customer satisfaction.

The remainder of the paper is organized as follows: First, we describe the research problem and our model. In Section 3 we present our simulation scenarios and the results. These are discussed in Section 4 before we conclude the paper in Section 5.

2. Research question and methodology

This study addresses a fundamental question for aviation: among the most common boarding strategies employed today, which one should an airline adopt for a given specific flight in order to improve operational efficiency and customer satisfaction? This question is addressed for two large commercial airplanes, 132 and 160 passengers, taking into account constraints such as limited space for carry-on luggage along with factors such as the airplane's passenger capacity, the quantity of carry-on items on board, passenger walking speed, as well as the time required to store luggage and resolve seat interferences.

The agent-based modeling (ABM) approach was selected for investigating this question because it allows for the quantification of airline performance and customer satisfaction from observations of virtual passengers behaving similarly to real passengers boarding a virtual airplane to scale. The ABM approach offers numerous advantages relevant to the present study, including: (i) a high level of interaction between entities and their environment [63], (ii) some degree of unpredictability and uncertainty [64], and (iii) the ability for entities to adapt their behavior and decision-making processes [65]. These features allow for the visualization of emerging behaviors and patterns, enabling a more thorough investigation of complex real-world systems [66].

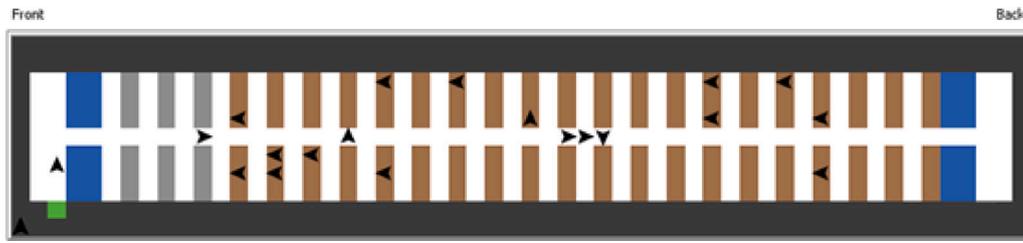


Fig. 1. Example of a boarding simulation run. Arrows indicate the passengers and their facing directions; white cells represent open spaces where passengers can walk freely, such as aisles and legroom; brown cells represent seats in the economy class; gray cells represent seats in the business class; blue cells represent airplane internal structures; the green cell represents the door. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.1. The agent-based model

The methodology adopted to build the simulation model follows the Overview, Design concepts and Details (ODD) protocol [67], which is frequently used for describing agent-based models (ABMs). The details are given next. The model was developed using Netlogo [68], an open-source programming software. For further information on the model, please refer to [69]. In the supplementary material, videos of the simulation are available.

2.1.1. Model purpose and patterns

The general purpose of the spatially-explicit agent-based model (ABM) presented here is to compare the performance of alternative airplane boarding strategies in terms of balancing airline revenue and customer satisfaction. Its specific purpose is to compare the performance of random, back-to-front and outside-in boarding strategies in 132-passenger and 160-passenger airplanes with respect to (i) total boarding time (TBT), (ii) individual boarding time (IBT) and (iii) maximum individual boarding time (MAXIBT).

2.1.2. Entities, state variables and scales

There are two types of entities in the model: (i) passengers, represented by mobile agents, and (ii) airplane structures, represented by stationary patches.

The state variables of the passengers are: (i) the passenger’s walking speed (SPEED), (ii) the time needed to store their luggage in the overhead bin (TIMELUG), and (iii) the time needed to resolve a seat interference, also known as seat shuffle time (SHUFFLE). These variables have identical values for all passengers. There are two additional characteristics that vary for each agent: (i) seat location (SEATPATCH), and (ii) luggage possession upon entering the airplane (LUGGAGE?); these variables are both randomly assigned according to a Bernoulli process, and describe that each passenger has a final destination in the cabin, and may or may not have exactly one piece of carry-on luggage.

The airplane model is based on a A320/B737 airplane cabin, which corresponds to a single-aisle layout of 3-3 seat configuration. A representation of the NetLogo interface is shown in Fig. 1. Some parameters defined by the user are: the maximum seat capacity (CAP), the number of rows reserved for business class passengers (BUSROWS), and the overhead bin capacity (BINCAPAC), defined as the maximum number of luggage pieces that a bin could hold per half-row. The time step in Netlogo is referred to as a ‘tick’ and is defined as 1/10 of a second (1 s = 10 ticks). Additionally, a patch in Netlogo, which corresponds to the unit area, is equivalent to 0.5 m × 0.5 m.

Table 1 lists the main variables used in the simulation, as well as their descriptions and units.

The flow rate (FLOWRATE) is defined here as a constant number of passengers entering the airplane door per minute, measured in pax/min. Our approximation to this rate is based on data from the literature [23]. Using the number of passengers and the times at which the first and last passengers boarded the airplane for each flight observation, it was possible to estimate an average flow rate for each occurrence. With the calculated flow rates, a regression curve

Table 1
Entities and state variables used in the boarding process simulation.

Entity	State variable	Unit	Description
Global	CAP	passenger	Maximum seat capacity in the airplane
	PAX	passenger	Number of passengers
	OCC	–	Flight’s occupancy level
	LUGPERC	%	Percentage of passengers carrying luggage at the beginning of boarding process
	BUSROWS	row	Number of rows designated to business class
	SPEEDREDUCT	–	Walking speed reduction factor for passengers walking in counterflow
	BINCAPAC	piece	Number of luggage pieces that an overhead bin can hold per half-row
	STRATEGY	–	Entering order of passengers
	FLOWRATE	pax/min	Number of passenger entering the airplane door per minute based on occupancy level
Passenger	SPEED	m/s	Maximum passenger’s walking speed
	TIMELUG	s	Time needed to store luggage in the overhead bin by a passenger
	SHUFFLE	s	Time needed to solve a seat interference by a passenger
	LUGGAGE?	boolean	Defines if passenger carries luggage
	SEATPATCH	patch	Patch referring to seat location
Airplane	BINCUR	pieces	Current number of luggage pieces in a overhead bin above a seat

of the flow rate versus expected flight’s occupancy level (OCC) was constructed (Fig. 2). The fixed value of flow rate used throughout the entire simulation is calculated at the beginning of each simulation run. However, and importantly, if there are passengers queuing close to the entrance door, for example because one or more are stowing their luggage, no new passengers will enter until there is free space. Thus, during the model run, the actual flow rate varies depending on local conditions. In real life, this rate is controlled at the boarding gate, where the agents check passengers’ tickets and IDs. Occupancy level is defined as the expected total number of passengers on the flight (PAX) over the seat capacity (CAP). For more information, please see [69]. Eq. (1) shows the function of the flow rate used in the model.

$$FLOWRATE(OCC) = \begin{cases} 16.797 - 9.015 * OCC, & \text{if } 0 \leq OCC \leq 1 \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

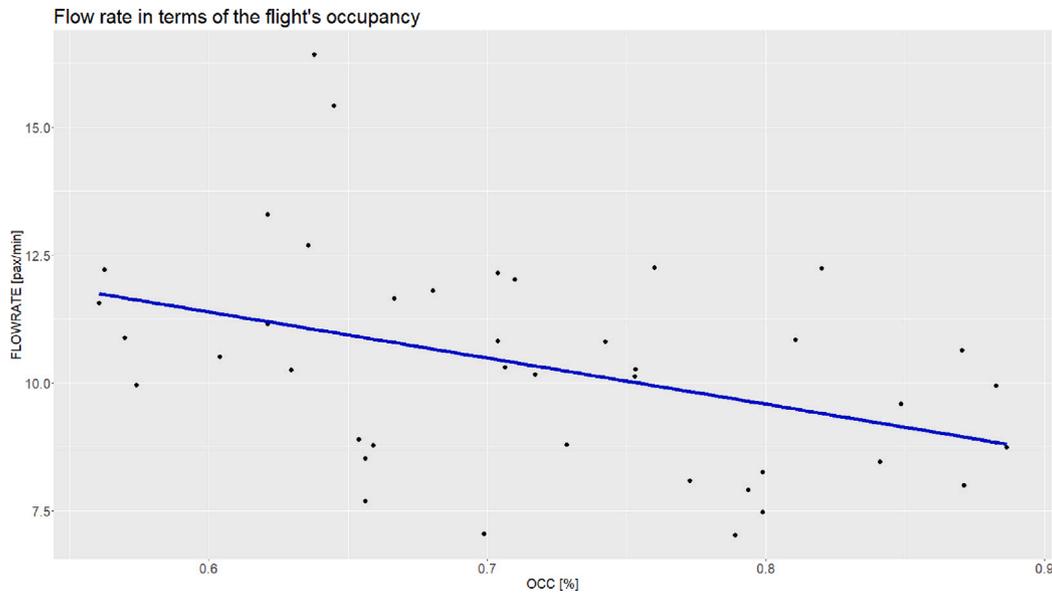


Fig. 2. Flow rates in terms of flight's occupancy level. The blue line represents the approximated regression function obtained and the black points are data from the observational study [12]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The simulation produces the following outputs: (i) total boarding time (TBT), (ii) individual boarding time (IBT), and (iii) maximum individual boarding time (MAXIBT), as previously defined. All three variables are analyzed in this paper, but we give special focus to TBT and MAXIBT because we believe they are the most predominant when comparing airline and passenger interests around the boarding process.

It is important to mention that in [59], IBT describes the entire time interval taken by a passenger from the moment he or she passes through the ticket check until he or she takes the assigned seat inside the cabin. However, since standing in the aisle of the airplane is the part of the boarding process that most bothers passengers [59], in the present paper, IBT only considers the time passengers wait standing in the cabin before taking their seats.

2.1.3. Process overview

The model's high-level algorithm proposed in this study is presented in Fig. 3.

The simulation starts with an empty airplane with the defined characteristics. Then, the following actions take place:

- At the beginning of the simulation, all passengers are generated, each being assigned to a random seat (SEATPATCH). Whether a passenger carries one piece of luggage or not is determined randomly according to a Bernoulli process. Then, all passengers are gathered and await their turn to board.
- In accordance with the selected boarding strategy and expected flight occupancy, the first passenger boards the airplane following the flow rate (Eq. (1)). Each passenger proceeds to their seat without making any mistakes (the passenger does not get lost inside the cabin, for example).
- Upon reaching their assigned row, the passenger carrying luggage checks the overhead bin of the same row and side where their seat is located. If there is space available, the passenger stands in the aisle for a certain period of time (herein TIMELUG) while stowing their luggage. During this time, other passengers cannot pass and must wait behind the person storing their luggage.
- If, conversely, the passenger reaches their assigned row and verifies the overhead bin above their seat is full, they will immediately discover the location of the nearest empty overhead bin, assuming perfect information about its location, as if they saw it straight away or cabin crew members were assisting them. The

passenger walks towards this nearest empty overhead bin, stores the luggage following the usual procedure, turns back towards their assigned seat and returns to it.

- When a passenger without luggage reaches their assigned row, they check for seat interference; in positive case, the passenger stands in the aisle for another period of time (called SHUFFLE) while the interference is resolved, meanwhile blocking the way of others.
- After resolving luggage storage and seat interference, the passenger is allowed to enter the row and to take their seat.
- If all overhead bins in the cabin are full, a passenger that is carrying a piece of luggage drops it and moves directly towards their seat without any time penalty, as if airline employees were at the entrance of the airplane controlling the bin capacity and checking in bags before the passenger enters the airplane.
- By default, passengers move along the cabin at maximum speed (SPEED). However, this speed can be adjusted. For example, if a passenger is standing in the aisle, the others must also stop and wait until this interference is resolved. If there is counterflow, i.e., two passengers passing each other in opposite directions in the aisle, SPEED is reduced by a factor given by SPEEDREDUCT for both passengers, until both have completed the passage.
- The next passenger is allowed inside the cabin according to FLOWRATE, which specifies a uniform rate of passengers entering the airplane door per minute, and follows the same process as the previous passenger. This process is repeated iteratively until all passengers have boarded.
- If the aisle is congested up to the door of the airplane, i.e., passengers are standing at the door and not moving forward, the passenger's boarding will be interrupted until the congestion is cleared and space is available inside the cabin. Passenger boarding will then resume.
- When all passengers are seated, the simulation ends.

2.1.4. Main model assumptions

The main assumptions are: (i) passengers enter the airplane one at a time, so there are no families or groups traveling together, (ii) passengers board over the bridge and only through one door at the front of the airplane, (iii) every passenger has an assigned seat, (iv) passengers cannot overtake each other when moving in the same direction, i.e., if there is a slower passenger ahead, the next passenger

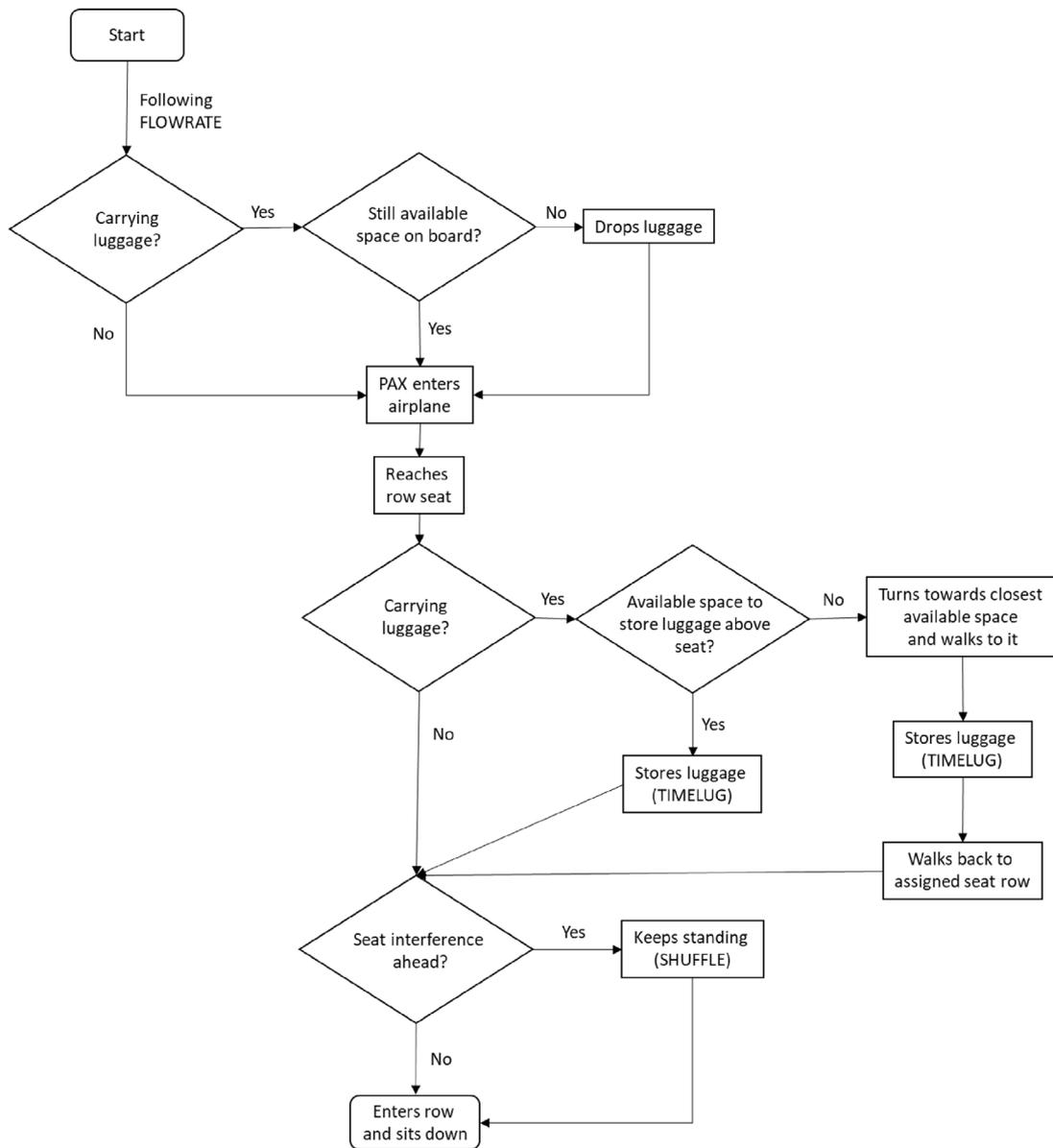


Fig. 3. Model’s high-level algorithm. All passengers move at a maximum speed (SPEED), which is reduced by a factor (SPEEDREDUCT) when two passengers are in counterflow.

must follow behind, (v) passengers make no mistakes regarding path or seat location; there are no delays either, which means that all passengers follow the rules and come on board at their assigned time and with their group, (vi) all carry-on luggage have the same size and format, and each passenger may or may not have one piece of luggage, (vii) the space in the overhead bin is limited, meaning that it may be insufficient for all passengers to store one luggage piece, (viii) as long as there is space available, carry-on luggage is always stowed in the overhead bins; as soon as all bins are full, the remaining passengers carrying luggage leave it at the airplane door so that it is transported to the airplane’s trunk, (ix) passengers have perfect information, i.e., if looking for available space, passengers always know where the closest empty bin is, (x) business class is not considered and passengers can only take a seat at economy class.

2.1.5. Output verification

The model has been thoroughly verified to ensure that it works as conceptually designed. The existing procedures in the code were

verified by individually testing code parts to check functionality and to make it as simple as possible. Verification was also done visually, given the visual element of the coding software, by checking whether the overall behavior of the passengers reflected what was expected of them.

2.2. Output validation

Simulation predictions were compared with results obtained from observations of real boarding processes in airplanes [23]. In this paper, the authors performed a statistical analysis of boarding times with respect to factors such as airplane capacity and number of luggage items on board. The data were collected by observing real boarding processes at a European airport. A total of 58 observations were obtained within several different airplane models and configurations. Considering only flights with occupancy above 50%, there are 13 observations for the 132-seat passenger airplane and six observations for the 160-seat passenger airplane, which are one of the largest data

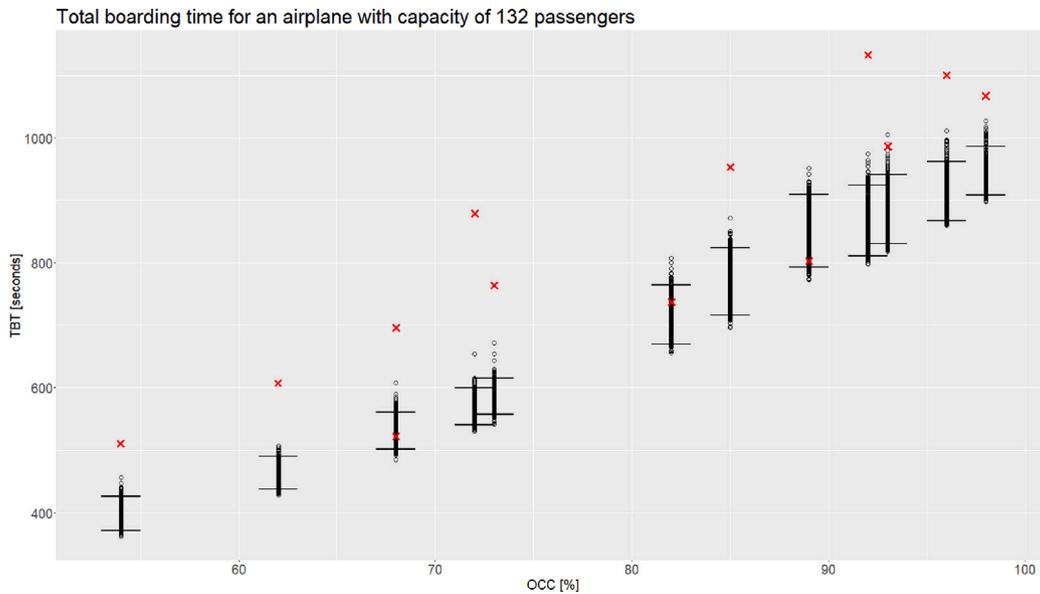


Fig. 4. Total boarding time for a 132-seat passenger airplane at different levels of occupancy. Points in red correspond to occupancy observations in the literature [23], and points in black are results obtained in the present simulation. Black bars shows the interval including 95% of simulation points. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2

Airplane models used for validation of the boarding process simulation [23].

Parameter	A319	A320neo
Maximum seat capacity	138	168
Maximum number of passengers	132	160
Number of business rows	3	4
Maximum number of passengers in economy class	120	144

Table 3

Nominal values of parameters used in the validation of the boarding process simulation.

Parameter	Value	Source
CAP	138 and 168 pax	[23]
OCC	According to Hutter et al. (2019)	[23]
LUGPERC	75%	[23]
BUSROWS	3 and 4 rows	[23]
SPEED	0.5 m/s	[70]
TIMELUG	13.9 s	[71]
SPEEDREDUCT	0.1	
SHUFFLE	10 s	[71]
BINCAPAC	2 pieces/half-row	[60]
STRATEGY	random	[23]

sets available. In order to validate the simulation built in this paper, two airplanes with the same configuration as those considered in the literature were examined, as shown in Table 2.

The data included flights with different numbers of passengers. In line with the adopted Ref. [23], business class seats were not considered in our simulation model because the boarding process only considered regular passengers, not including priority passengers. All observed boarding events used the random boarding strategy, which means that passengers did not follow any particular order and boarded on a first-come, first-served basis.

Other parameter values used in our simulations are given in Table 3. Nominal values were taken from the literature and have not been calibrated.

The simulations were run 1000 times for each instance, giving a total of 12,000 runs for the 132-seat passenger airplane and 5000 runs for the 160-seat passenger airplane to ensure statistical relevance, due to the randomness introduced by passengers boarding order and seat assignment. Each data point used for validation was selected based on the flight data with unique occupancy levels above 50%, resulting in

12 data points for the 132-seat passenger airplane and five data points for the 160-seat passenger airplane. Compared to real observations, the simulation results showed a tendency to speed up boarding (Figs. 4 and 5). To assess the agreement between the simulation results and the data points, we quantified how different the average of each analyzed case was from its respective observation. On average, the results for the 132-passenger airplane differed by 17% and for the 160-passenger airplane by 16% from the observed data. Although the simulated results do not fully match the real data, a similar trend can be observed. Although our simulation results are in good agreement with the real data, because the sample is rather small we recommend the results herein to be interpreted with caution.

Additional input data are available in the literature, such as flow rate [71,72] or walking speed [44,71,73]. Various validation scenarios for different values of walking speed (SPEED) were considered in order to investigate the impact of different parameter values on the results, as well as to showcase our model’s capability to produce results that are closer to reality (Figs. 6 and 7).

Nonetheless, we opted for using as the nominal values for the simulations input data from sources that provided a well-documented description of their experimental data collection processes.

3. Simulation scenarios and results

This section presents the results obtained from the simulated scenarios and the sensitivity analysis. The results in the main text refer to a 132-seat passenger airplane, while those for the 160-seat passenger airplane are presented in Appendix A. Each scenario was run 1000 times. The parameters used for this assessment are shown in Table 4.

The data post-processing was performed in RStudio, using the R programming language. In order to do that, the output file generated by Netlogo was read into RStudio. Besides the standard RStudio built-in functions, the following libraries were used: (i) *tidyverse* and *dplyr*, for data manipulation, (ii) *ggplot2* and *ggpubr* for plot creation, (iii) *colorBlindness* and *viridis*, for plot color manipulation, and (iv) *FSA*, for hypothesis testing. To compare distributions, non-parametric statistical tests were used, including: (i) the Wilcoxon test to compare two distributions, (ii) the Kruskal–Wallis test to determine if one of the analyzed distributions differed from the others, and (iii) Dunn’s test, to determine which of the non-parametric distributions differed from

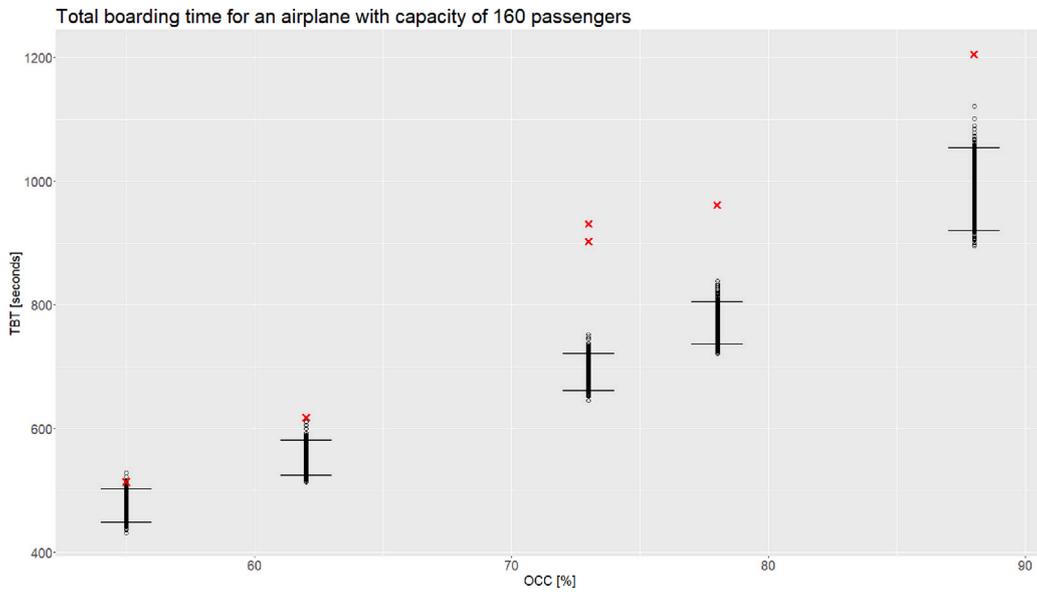


Fig. 5. Total boarding time for a 160-seat passenger airplane at different levels of occupancy. Points in red correspond to occupancy observations in the literature [23], and points in black are results obtained in the present simulation. Black bars shows the interval including 95% of simulation points. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

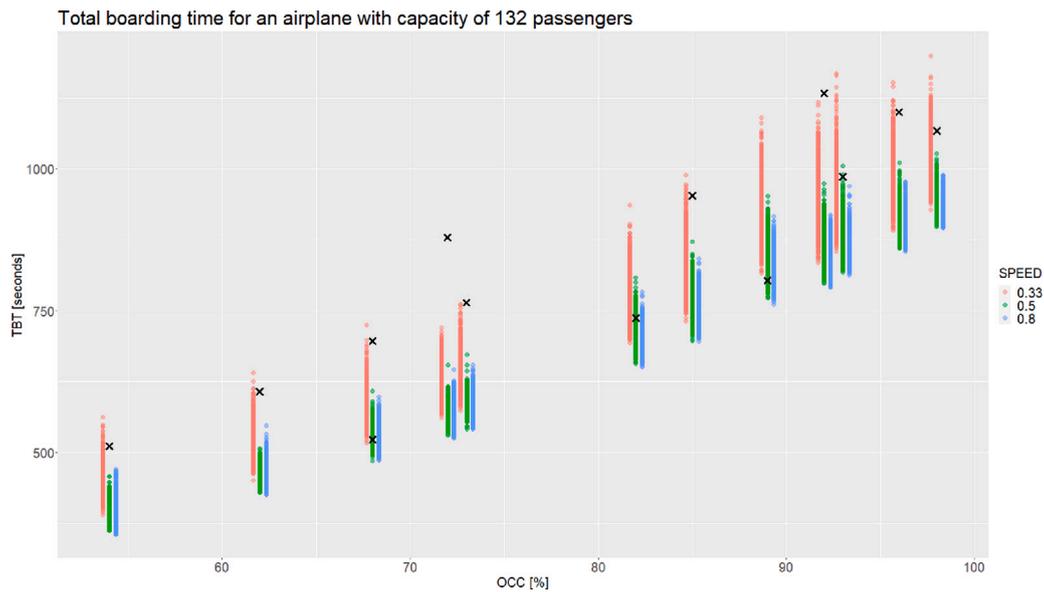


Fig. 6. Total boarding time for a 132-seat passenger airplane at different levels of occupancy and walking speed. Points in black correspond to occupancy observations in the literature [23]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 4
Nominal values of parameters used in the boarding process simulation.

Parameter	Value	Source
CAP	138 and 168 pax	[23]
OCC	100%	Worst case scenario
LUGPERC	75%	[23]
BUSROWS	3 and 4 rows	[23]
SPEED	0.5 m/s	[70]
TIMELUG	13.9 s	[71]
SPEEDREDUCT	0.1	
SHUFFLE	10 s	[71]
BINCAPAC	2 pieces/half-row	[60]
STRATEGY	random, back-to-front and outside-in	[23]

each other. The significance level was considered to be 5% ($\alpha = 0.05$). Local Sensitivity Analysis [74] was performed in order to evaluate how changes on a particular input affect a given output. It was carried out by applying small perturbations around nominal values of inputs, one-factor-at-a-time.

3.1. Simulated scenarios

Following the verification and the validation stages of the simulation model, we explored various scenarios in order to investigate the effect of the boarding strategy on total boarding time and individual boarding time. Three different boarding strategies were examined: (i) random, (ii) back-to-front, and (iii) outside-in. These strategies were selected because they are among the most commonly used boarding strategies used by airlines today.

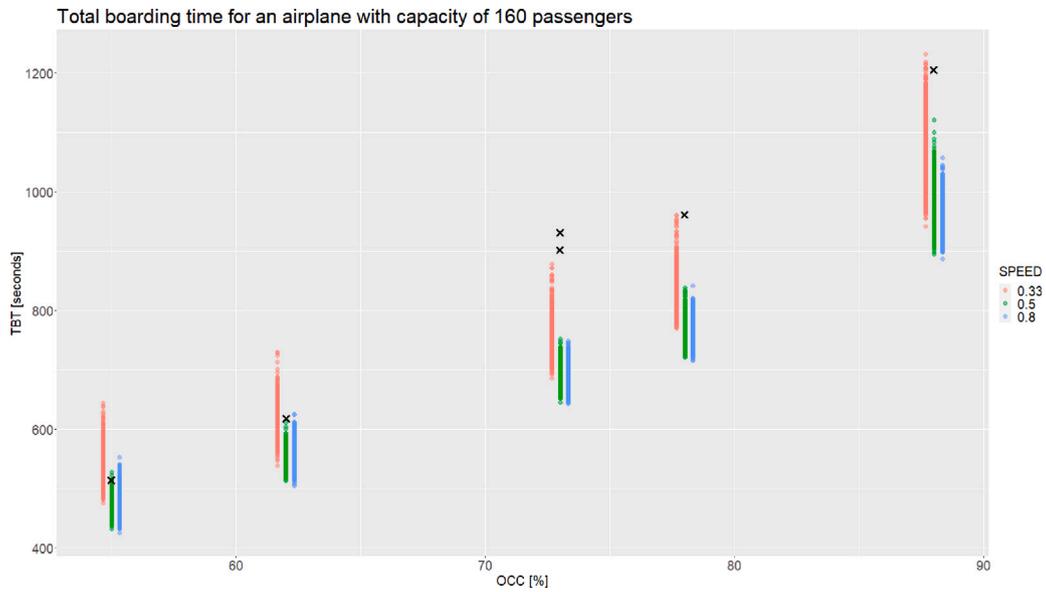


Fig. 7. Total boarding time for a 160-seat passenger airplane at different levels of occupancy and walking speed. Points in black correspond to occupancy observations in the literature [23]. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

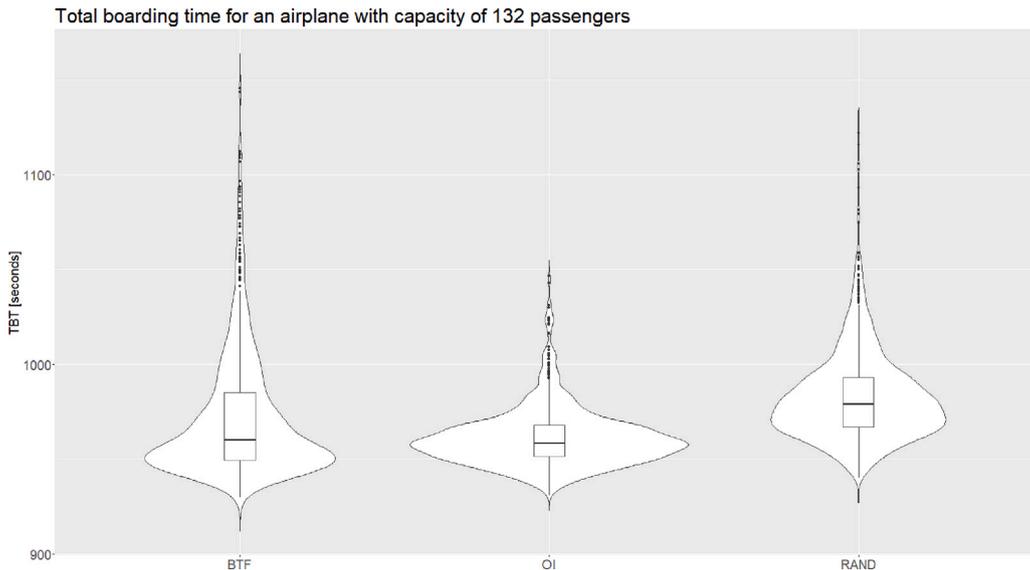


Fig. 8. Total Boarding Time (TBT) in terms of boarding strategy on a 132-seat passenger airplane (RAND = random, BTF = back-to-front, OI = outside-in).

Random boarding means that no specific order is used and passengers enter on a first-come-first-served basis. When back-to-front boarding strategy is adopted, it means that passengers are separated into three groups, and come on board in an order dependent on their seat locations: the passengers on the group that will board first have seats assigned to the back of the cabin; the next group of passengers have their seats in the middle of the cabin and, finally, the last group to enter the airplane are those passengers assigned to seats at the front of the cabin. Within each group, the order is random. When outside-in boarding strategy is used, passengers are also separated into three groups based on their seat locations; however, in this case, the groups are separated according to the seat locations relative to their proximity to the windows: the first group to board is the window seat group; then, the group of passengers assigned to middle seats; and, finally, the last group to come on board are those passengers assigned to aisle seats. Again, within each group, the order of passengers is random. For all these three strategies, passengers always enter through the front door of the airplane.

3.2. Simulation results

Concerning total boarding time, random boarding was the slowest strategy, with the largest median time, followed by back-to-front and then outside-in (Fig. 8). A Dunn’s hypothesis test showed that the medians of all distributions differed ($p\text{-value} < 2.2e-16$, $\alpha = 0.05$), though by a small amount. Random boarding had a median of 978.85 s, while back-to-front and outside-in had practically the same result (960.07 s for back-to-front and 958.40 s for outside-in, with a difference of about 2 s between them). The averages of TBT for each strategy were: 961.37 s for outside-in, 972.25 s for back-to-front and 982.86 s for random. As the distributions are highly skewed, we decided to evaluate the results through the median because it is a centrality statistics, giving a more accurate interpretation. Also, results suggested that the outside-in strategy presented the smallest deviation (15.56 s in comparison to back-to-front’s 33.52 s) and the shortest upper tail among the three strategies.

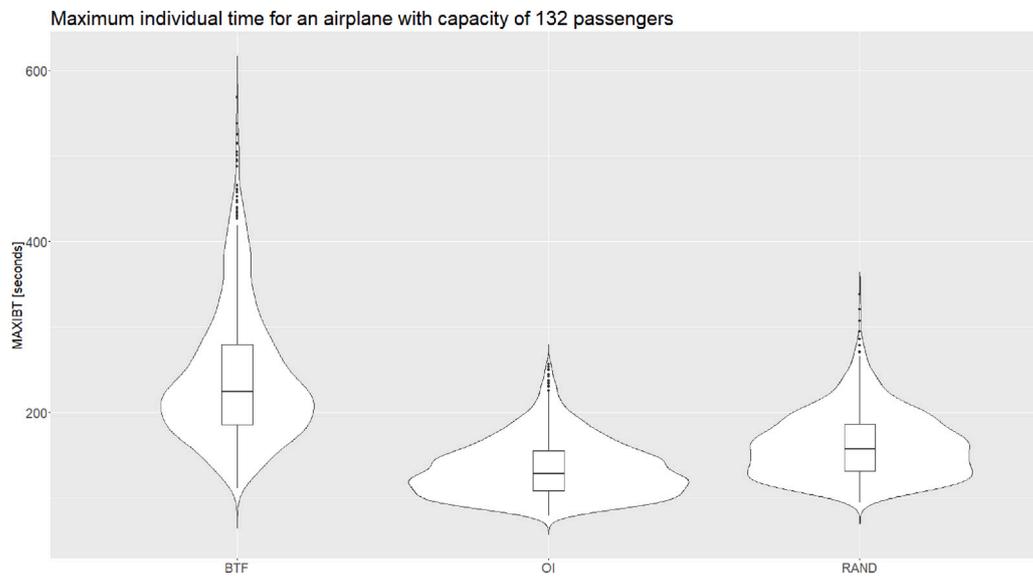


Fig. 9. Maximum Individual Boarding Time (MAXIBT) in terms of boarding strategy on a 132-seat passenger airplane (RAND = random, BTF = back-to-front, OI = outside-in).

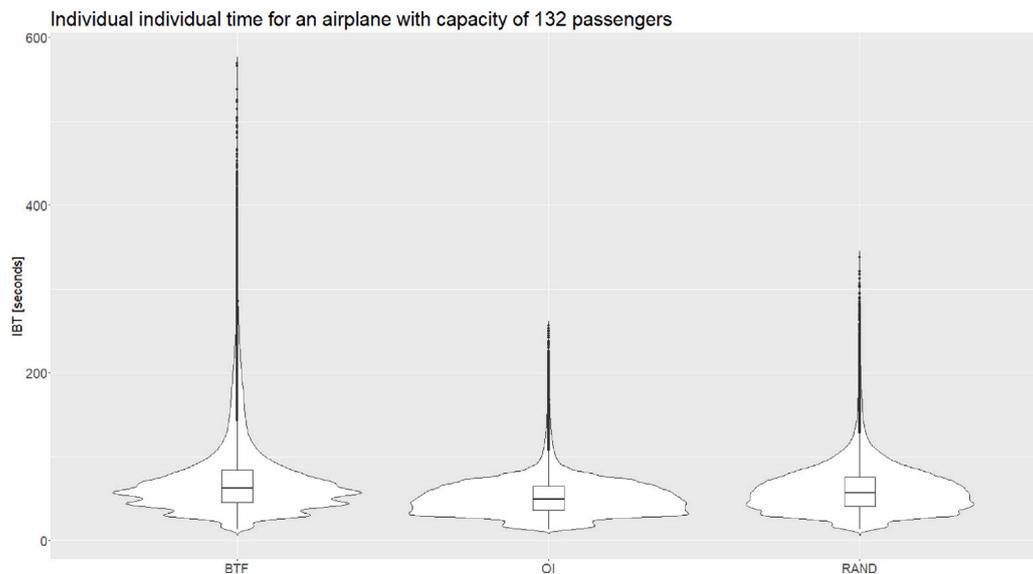


Fig. 10. Individual Boarding Time (IBT) in terms of boarding strategy on a 132-seat passenger airplane (RAND = random, BTF = back-to-front, OI = outside-in).

The strategy back-to-front had the highest maximum individual boarding times (MAXIBT), with a median of 224.17 s (3.74 min), while the outside-in strategy had the lowest median with 128.32 s (2.14 min) (Fig. 9); a difference of more than one minute (57% faster). The median for random boarding was 157.12 s (2.62 min). The averages of MAXIBT for each strategy were: 134.27 s for outside-in, 161.53 s for random and 241.21 s for back-to-front. A Dunn’s hypothesis test showed all medians were different ($p\text{-value} < 2.2e-16$, $\alpha = 0.05$). Back-to-front had the highest variability.

Regarding individual boarding times, all medians were similar at about 49–62 s (Fig. 10). Dunn’s hypothesis test showed no difference between the highest and the lowest median values, which are those of back-to-front and outside-in ($p\text{-value} < 2.2e-16$, $\alpha = 0.05$). The averages for IBT were 52.12 s for outside-in, 61.23 s for random and 74.32 s for back-to-front. Also, all distributions were highly skewed. Therefore, even though most passengers were subjected to approximately one minute standing, there were a considerable number of cases of passengers with longer standing times, with a maximum of 569.20 s

(9.49 min). This is an important performance indicator for airlines, as this passenger will probably be highly dissatisfied.

In order to better understand this indicator, heat maps are presented for each boarding strategy considering medians, standard deviations (SD) and maximum values for each seat in the cabin. Heat maps show results as colors, making it easy to visualize over space. The color scheme used is color blind friendly. Considering random boarding, passengers with seat locations at the back of the airplane were subjected to the longest medians of individual boarding time (around 80 s), which makes sense since they had to walk longer distances (Fig. 11). Overall, the standard deviations were evenly distributed throughout the cabin with values around 29 s. Maximum values were also distributed around the cabin, with values reaching 338 s.

Implementing back-to-front boarding, the back seats within each boarding group (front, middle and back) had higher median individual boarding times compared to other seats in the groups (Fig. 12). This could be explained by interferences from previous groups affecting the new group entering the airplane, either from congestion due to

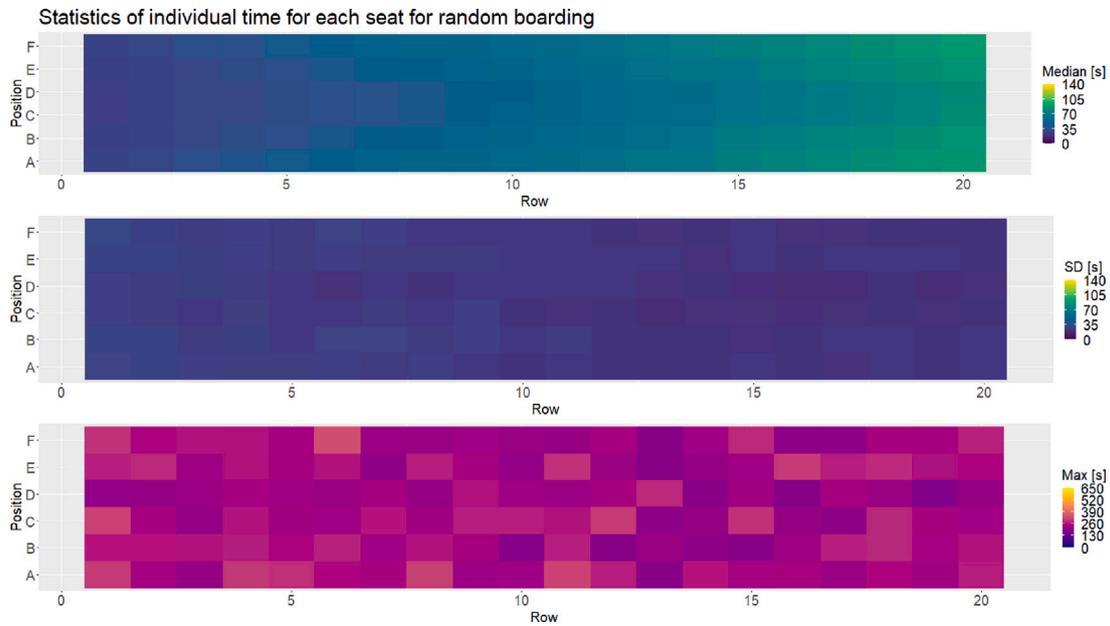


Fig. 11. Individual Boarding Times (IBT) in seconds per seat for random boarding on a 132-seat passenger airplane.

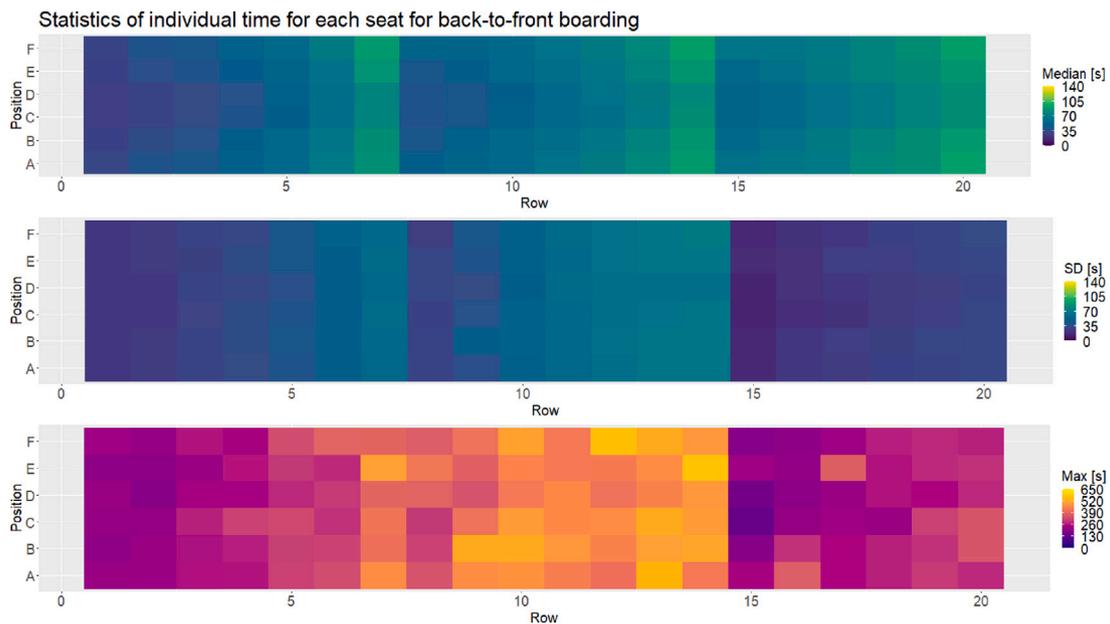


Fig. 12. Individual Boarding Times (IBT) in seconds per seat for back-to-front boarding on a 132-seat passenger airplane.

passengers storing their luggage or looking for available bins. Standard deviations were up to 71 s, especially in the middle sector. This higher variability can be explained by the luggage capacity of the cabin. When the middle group was entering, part of the overhead bins were already filled, and therefore, this group had to seek available space towards the front of the airplane. When the front group entered (last group to board), most of the bins were already full, so some of the passengers had to walk shorter distances to stow their luggage, and some entered already without luggage, having given it away, thus reducing their individual boarding times due to less interference. Longer maximum values were concentrated in the middle sector, with values of up to 570 s.

The outside-in boarding strategy produced longer individual boarding times for passengers sitting at the back of the airplane, with medians around 66 s, standard deviations of up to 10 s and longer variations for the aisle seats (Fig. 13). This indicated a certain stability

in individual boarding times for most passengers. Lastly, aisle seats reached maximum values of up to 256 s.

In the violin plots, it was already shown that the distributions of the individual boarding times were highly skewed. With the heat maps, it was possible to see patterns according to the seat location in the cabin. The medians for each strategy were very similar, but their distribution through the airplane was highly affected by the ordering of passengers. The same can be seen for the maximum values. Back-to-front boarding had longer tails in the violin plot, but these values were mostly concentrated in the middle sector. On the other hand, outside-in not only had the lowest values, but they were also distributed along the cabin.

For comparison with the current scientific literature, where bin capacity is usually not a limiting assumption, simulations were also run considering an overhead bin with enough capacity for all passengers to bring one piece of luggage (BINCAPAC = 3 bags/half-row). By running a Wilcoxon test and comparing each strategy with different bin

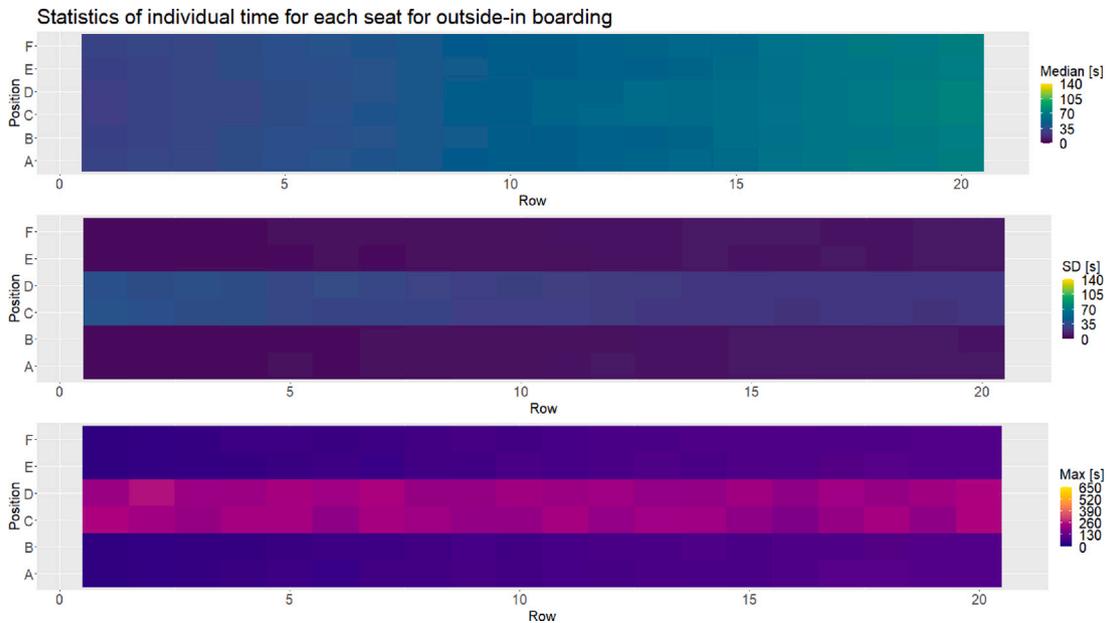


Fig. 13. Individual Boarding Times (IBT) in seconds per seat for outside-in boarding on a 132-seat passenger airplane.

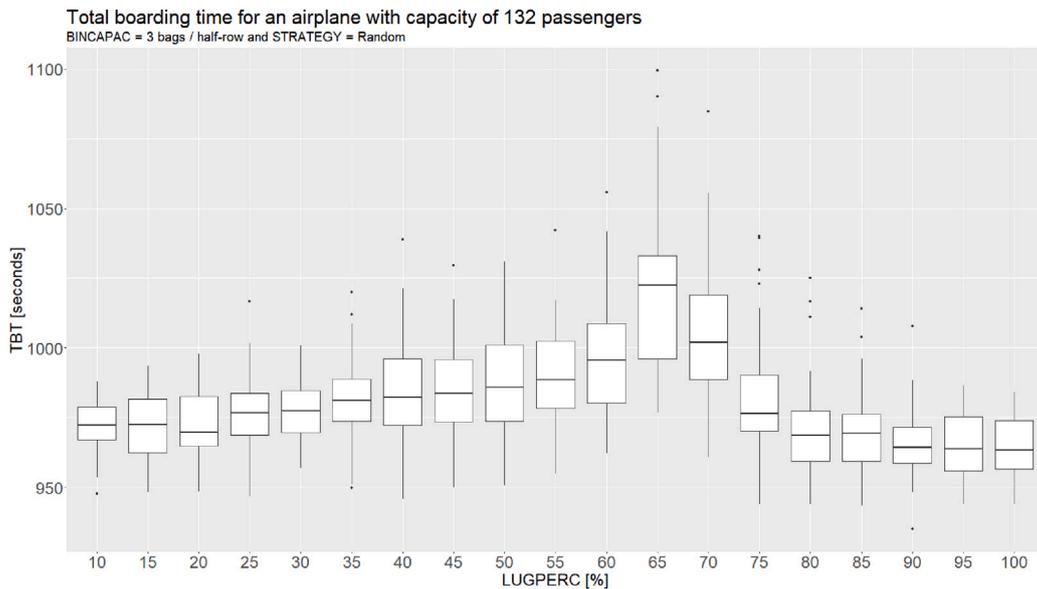


Fig. 14. Total Boarding Time (TBT) in terms of percentage of passengers carrying luggage (LUGPERC) for a 132-seat passenger airplane.

configurations (with and without enough capacity), all medians of total boarding times (TBT) were different (p -values $< 2.2e-16$, $\alpha = 0.05$). However, they were not highly affected by this assumption, differing by less than 2.84% for a 132-seat passenger airplane and 2.07% for an 160-seat passenger airplane with regards to the corresponding limited bin experiments. On the other hand, maximum individual boarding times (MAXIBT) did show important differences (p -value $< 2.2e-16$, $\alpha = 0.05$). When random boarding was used in a 132-seat passenger airplane with limited bins (BINCAPAC = 2 bags/half-row), the maximum individual boarding time was 338.05 s (5.63 min); with bins with enough capacity, this was reduced to 171.90 s (2.86 min) (a 50.8% reduction). The same trend was seen for back-to-front boarding (569.20 s with limited bins and 198.55 s with bins with enough capacity, a 34.8% reduction) and outside-in boarding (256.40 s with limited bins and 106.00 s with bins with enough capacity, a 41.3%

reduction). For the 160-seat passenger airplane it is similar with the bin with enough capacity causing a reduction of 50.7% for random, 33.2% for back-to-front and 38.0% for outside-in boarding, when compared to limited bins. These results highlight the importance of this assumption for customer satisfaction metrics.

3.3. Sensitivity analysis

Local sensitivity analyzes (LSA) were performed on three outputs: (i) total boarding time (TBT), (ii) individual boarding time (IBT), and (iii) maximum individual boarding time per run (MAXIBT). A LSA was performed for each parameter, while keeping others at their nominal values.

In the LSA, the parameter that produced the most interesting results was the percentage of passengers carrying luggage (LUGPERC). LSA

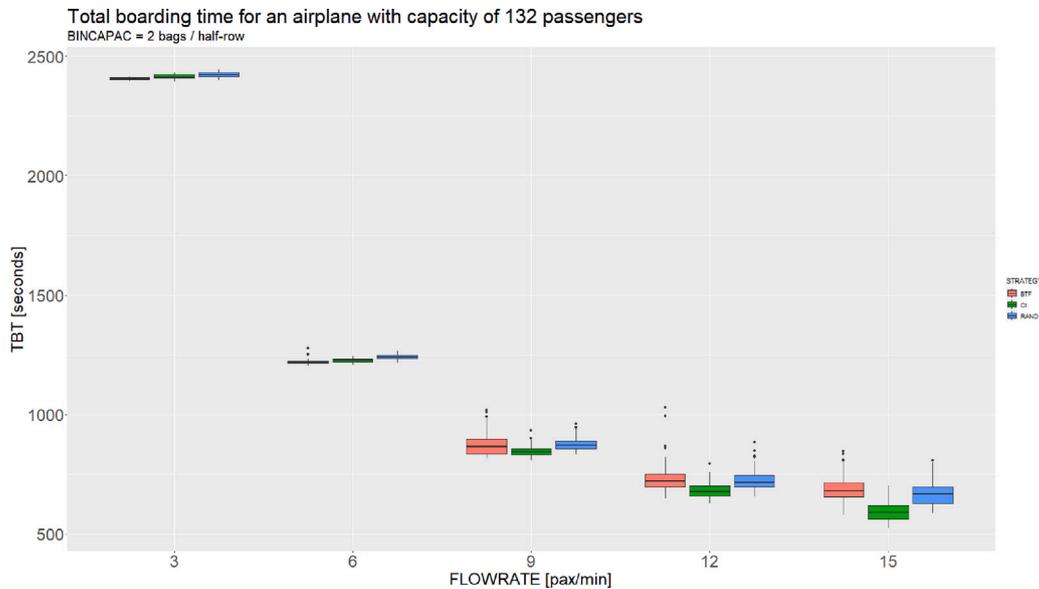


Fig. 15. Total Boarding Time (TBT) in terms of passenger's entrance rate (FLOWRATE) for a 132-seat passenger airplane.

showed a critical transition in the behavior of the system associated to LUGPERC and it was marked by the moment the bins filled up. When the chosen percentage of passengers with luggage (LUGPERC) was lower than the cabin capacity (BINCAPAC), i.e., there was enough space for passengers to bring their luggage, the increase in LUGPERC resulted in an increase in total boarding time (TBT) (Fig. 14). However, when the chosen level of LUGPERC was greater than the bin capacity, i.e., there was insufficient space in the airplane (above LUGPERC equal to 66%), an increase in LUGPERC resulted in a decrease in TBT. This may seem counter-intuitive, but once the bins reached capacity, the boarding process was significantly accelerated due to the lack of aisle interferences as passengers boarded without luggage. Also, as LUGPERC increased, the bins filled earlier, so this first part of the process was also faster.

A LSA was also conducted to evaluate the effect of FLOWRATE in each of the boarding strategies studied. In the simulated scenarios already presented, given that the occupancy was fixed at 100%, the FLOWRATE was established as 7.7 pax/min. Therefore, for the present analysis, FLOWRATE was varied between 3 and 15 pax/min. With the increase of FLOWRATE, total boarding time greatly decreases (Fig. 15). It is also possible to see a shift in the results as FLOWRATE increases. At lower levels, back-to-front performed better than outside-in and random boarding. However, with the increase of the rate of passengers entering, back-to-front took longer than the other strategies and outside-in became the faster option. This demonstrates the importance of this parameter for the boarding operations, i.e., the boarding strategy efficiency depends on the entrance rate of passenger through the airplane door.

These results can be explained due to the spacing between passengers entering the airplane. At lower levels of FLOWRATE, passengers are more spaced out, i.e., more time passes until a passenger may encounter another, which results in less interferences. That is why the results are so similar for all strategies at FLOWRATE equals 3 pax/min, for example. The boarding strategies influences are alleviated. However, when FLOWRATE is high, there will be more interferences, which is why back-to-front performed worst and outside-in best.

This analysis was also conducted in terms of MAXIBT (Fig. 16). Here, the strategy back-to-front always performed worst and outside-in best, regardless of FLOWRATE levels. With the increase of the parameter, the individual boarding times for back-to-front increased at

a higher rate than other strategies. Therefore, when considering this aspect, FLOWRATE does not affect the output pattern.

Given the uncertainty associated with the reference values of the model inputs, the variability in the outputs was considerable. However, when comparing different scenarios with the same inputs, the difference in output was relevant, indicating that these results were qualitatively important.

4. Discussion

When comparing three boarding strategies in this study, outside-in yielded the lowest median for total boarding time (TBT) in a 132-passenger airplane, followed by back-to-front and then by random boarding, though the largest difference between medians represented only 1.92% of the longest boarding time (Fig. 8). Interestingly, however, back-to-front yielded the greatest variation in TBT, and most of the longest maximum individual boarding times (Fig. 9). Back-to-front boarding also produced the largest disparity of individual boarding times (IBT) among seating positions with the middle boarding group being subject to the largest values (Figs. 11 to 13). These high values for back-to-front boarding occurred because the overhead bins at the rear of the airplane filled early, forcing passengers with seats at the rear of the airplane to search for available overhead bin space further forward in the airplane. This consumed walking time, often at a slower speed owing to aisle congestion. The outside-in boarding strategy, in turn, showed the least variation in the three outcomes (TBT, IBT, and MAXIBT), as well as the least time difference between passenger seating positions (Figs. 13).

Unfortunately, owing to differences in the underlying assumptions made between our models and models from current scientific literature, such as inclusion of variability in passenger walking speed [70,71,73], in number of groups divisions [54,75,76], in passenger's entrance rate [71,72], in luggage pieces carried [28,54], in luggage storage time [20,28,54,62,71] or in overhead bin capacity [62], it is difficult to compare results objectively.

Our study showed that outside-in boarding strategy produced the shortest total boarding time (TBT), agreeing with current literature [55, 57,58]. However, it is suggested that back-to-front performs better than random boarding in terms of total boarding time (TBT), which may contrast with general consensus in previous scientific literature,

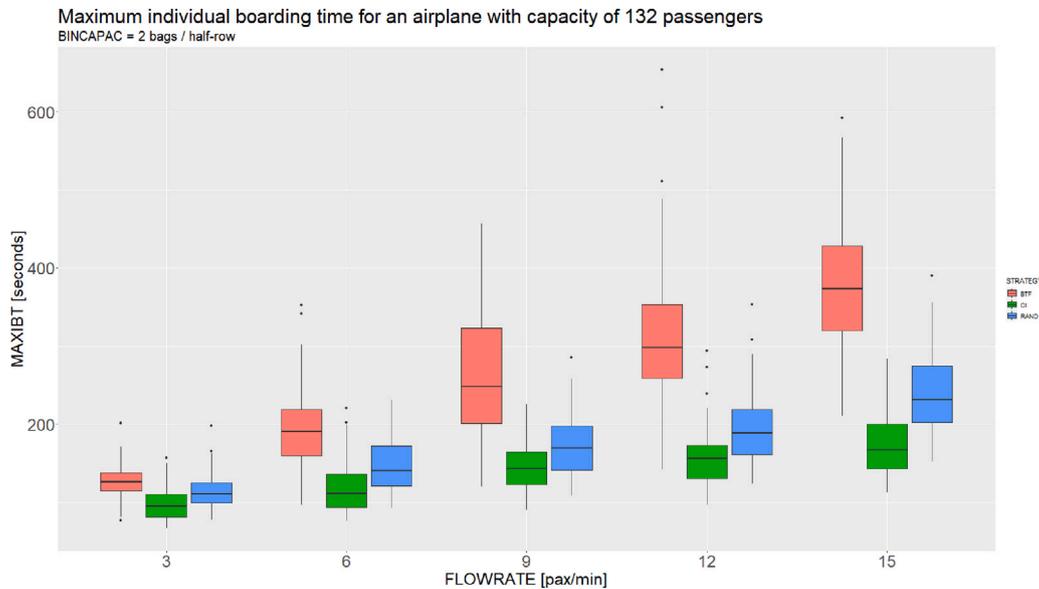


Fig. 16. Maximum Individual Boarding Time (MAXIBT) in terms of passenger's entrance rate (FLOWRATE) for a 132-seat passenger airplane.

i.e., back-to-front produces longer total boarding time in comparison to random boarding [28,44,53,55,56]. Thus, our study also showed that back-to-front produced the longest individual boarding time (IBT), which is also in agreement with current scientific literature [20,28,44].

The main difference in the results for total boarding time (TBT) can be explained by the different assumptions in the model. Note that this model assumes that the airplane has a finite overhead bin and that passengers can only carry a limited number of bags, i.e., there is not enough space for all passengers to bring a bag on board. This is an aspect that, to the best of our knowledge, has not been considered in the scientific literature, with the most common solution being to increase the storage time in terms of the number of bags carried [18,33,44,61,62]. Including this assumption in the model not only made it more realistic but also greatly affected the performance of the strategies, as passengers moved more around the cabin looking for bin space, creating counterflow and congestion.

With regard to the implementation of boarding strategies, it must be noted that different advantages, disadvantages and challenges arise here. Random boarding is the easiest to implement, as no boarding groups need to be formed, but this boarding strategy creates a feeling of disorganization and stress, especially among US passengers [59]. As far as back-to-front is concerned, the number of groups must be decided (which in turn has an influence on the performance of the strategy). Outside-in brings with it the problem that passengers traveling together and seated next to each other are initially in different boarding groups and it must be decided how to deal with this and whether to simply let them board together in one of the assigned groups (here it can be assumed that they will not block each other).

Of course, like any model, our model has some limitations. First, it was designed for a single-aisle airplane. Also, all passengers were considered equal, meaning that they all followed the same rules and had the same behavior. There were no children or passengers with special needs. Passengers also traveled alone; so group dynamics were not anticipated in this model and no disruption happened due to group separation depending on the boarding strategy. Individuals were considered to know and follow the procedures; therefore, there were no disturbances due to errors or failure to follow protocol. Passenger's bags had all the same shape and size, which facilitated the building of the model, but does not reflect real life. Another consequence of this assumption is that the model does not take into account the dynamics of luggage rearrangement in the overhead bins, which could

take more time to solve the interference. Priority boarding was also not considered, which would have resulted in some seats being taken before the first regular passenger boarded. Passengers were allowed inside the cabin in a uniform rate and there were no late passengers, as it was assumed that all passengers were waiting at the gate as soon as the process started. Nevertheless, our model is a good approximation to reality and allows assumptions that have not yet been represented in simulation models for airplane boarding (such as the limitation of the capacity of the overhead bins).

5. Concluding remarks

In this paper, we presented an agent-based model of the boarding process in a commercial airplane. Verification and validation with independent data were described, and an application to a real-world situation was illustrated. As an agent-based simulation allows modeling diverse agents, it was also possible to evaluate their individual outputs, such as individual boarding times, i.e., how long did passengers have to stand inside the airplane cabin. This was valuable in assessing not only an airline's operational efficiency, but also its level of service to customers (since for passengers the time they have to stand in the aisle on the airplane is one of those that bothers them the most).

The objective of this work was to analyze which boarding strategy, among those most commonly used by airlines today, best balances both operational efficiency and customer satisfaction indicators, here assessed by total boarding time (TBT), individual boarding time (IBT), and maximum individual boarding time (MAXIBT). The results showed that although the back-to-front strategy did not produce the worst median total boarding time (TBT), it had the longest upper tail. This means that although this strategy in some level produced good results, it risked leading to one of the longest boarding times of the strategies studied. In comparison, the strategy outside-in produced the best median total boarding time and the shortest tails, indicating that this strategy was more robust. Thus, in an operational efficiency context, outside-in seemed to be the best option. Regarding maximum individual boarding times (MAXIBT), the response pattern changed, with back-to-front producing the highest median individual boarding times and the longest upper tail. In this case, outside-in had the lowest median and a more centered distribution, which also made this strategy the best option in terms of customer satisfaction. Therefore, when considering the proposed research question, i.e., which commonly used

boarding strategy would balance operational efficiency and customer satisfaction, the best solution would be outside-in, as it leads to the best combination of results for the total boarding time and the individual boarding time.

The limitations in our model could be objects of future studies. For example, as illustrated by the results for a 160-seat passenger airplane (Appendix A), the agent-based model presented here was capable of simulating airplanes with different sizes and row configurations. Our model moreover allows for the design of unique passengers in terms of walking speed, time needed to store luggage, time needed to solve an interference, number of bags carried, size and shape of bags carried and group assignment, which can be accomplished by creating probability distributions for each aspect. Another customization can be on the level of patience in following protocol and possibility of making mistakes inside the cabin. Impatient passengers may try to board before their assigned boarding group. On the other hand, these individuals may choose to board last in order to spend less time inside the cabin. This can also be modeled by a probability of not following protocol and choosing another time to board. For the mistaken passenger, despite having the seat location in hand, he or she may mistakenly try to sit in another seat, causing a disruption, either by causing congestion in the airplane aisle or by causing unnecessary seat interference with the correct occupants of the seat in question. Thus, passengers could be allowed to enter the airplane by a more realistic process, such as Poisson instead of uniform. The model can also be used to compare even more boarding strategies by implementing new strategies or different versions of known strategies. For example, reverse pyramid could be implemented or in a back-to-front strategy, passengers can be separated into more than three groups. The agent-based model makes it a potentially valuable tool for achieving the critical yet delicate balance between reducing airplane boarding times and improving customer satisfaction.

CRedit authorship contribution statement

Bruna H.P. Fabrin: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Denise B. Ferrari:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Eduardo M. Arraut:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Simone Neumann:** Writing – review & editing, Validation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

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Appendix A. Supplementary material: Simulated scenarios

In this section, results of the 160-seat passenger airplane are presented.

Random boarding was the slowest strategy on median, followed by outside-in and back-to-front (Fig. A.17). When performing a Dunn’s hypothesis test, all medians of distributions were different from each other (p -value = $1.52e-11$, $\alpha = 0.05$). However, it is important to state that the differences between them were small. Random boarding had a median of 1170.10 s and back-to-front of 1149.52 s, a difference of about 21 s. The averages of TBT were 1175.89 s for random, 1166.63 s for back-to-front, and 1154.14 s for outside-in. Also, the distribution of back-to-front strategy, even though had the smallest median among the three, also had a long tail, indicating a presence of cases of longer total boarding times (TBT).

The back-to-front strategy had the highest maximum individual boarding time (MAXIBT) with a median of 273.77 s (4.56 min), followed by random and outside-in boarding (Fig. A.18). The averages of MAXIBT were 156.82 s for outside-in, 183.53 s for random and 293.29 s for back-to-front. The difference between the highest and lowest median was about 2 min. Through a Dunn’s hypothesis test, all medians were different (p -value < $2.2e-16$, $\alpha = 0.05$). Back-to-front presented the biggest variability among the three strategies. Therefore, even though this strategy produced the shortest boarding process, passengers may have had to stand for longer times.

The lowest median of individual times was presented by the outside-in strategy, followed by random and back-to-front (Fig. A.19). Through a Dunn’s hypothesis test, back-to-front and outside-in medians were not the same (p -value = 0, $\alpha = 0.05$). Still, all medians had similar values: the highest mean was 70.65 s and the lowest was 55.90 s. It is important to stress that all distributions were highly skewed. Therefore, even though most passengers should expect a minute of standing up, there were a significant number of cases in which passengers were subjected to longer times. For example, the maximum time obtained was of 636.70 s (10.61 min). This was an extreme value, but it was a relevant indicator for customer satisfaction, as this individual will likely be extremely unsatisfied.

Then, heat maps were presented to show how the outputs perform spatially in the airplane cabin. When random boarding was used, the overall behavior was similar to the smaller airplane (Fig. A.20). As expected, individual times were higher as the airplane was longer, with values up to 100.6 s. Standard deviations were up to 35.66 s and distributed evenly around the cabin. And maximum values were also scattered along the airplane, with values up to 374.9 s.

The back-to-front strategy provided longer medians for IBT up to 109.3 s (Fig. A.21). Higher standard deviations were mainly concentrated in the middle section, with values up to 90.93 s and maximum values were also seen in the middle of the airplane, with values up to 636.7 s.

Lastly, when outside-in boarding was used, medians were the smallest among all strategies, with values up to 89.52 s (Fig. A.22). Standard deviations were small throughout the cabin, with bigger values up to 45.46 s for passengers seating in the aisle. Following the same pattern as the smaller airplane, worst cases of IBT were distributed along aisle seats with values up to 314.2 s.

When comparing the three strategies, back-to-front generated the worst outputs. Not only it had the highest values of individual boarding times, but also the highest standard deviations, specially in the middle sector of the airplane. This means that, even if this strategy produced the smallest total boarding times, passengers could be subjected to the longest individual times. Therefore, the airline would have to balance operation efficiency with customer satisfaction in this case.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.orp.2024.100301>.

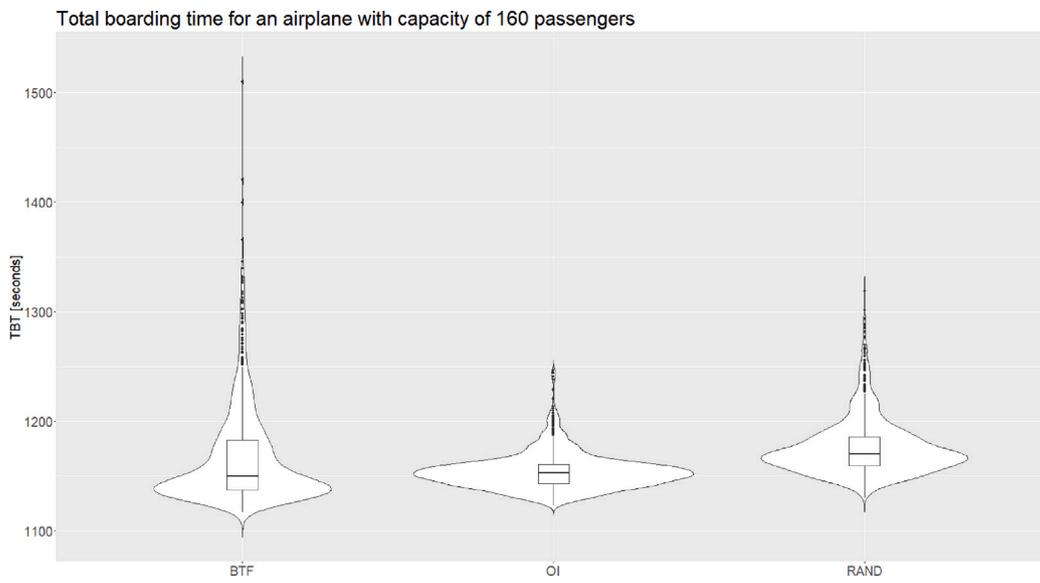


Fig. A.17. Total Boarding Time (TBT) in terms of boarding strategy (STRATEGY) for a 160-seat passenger airplane (RAND = random, BTF = back-to-front, OI = outside-in).

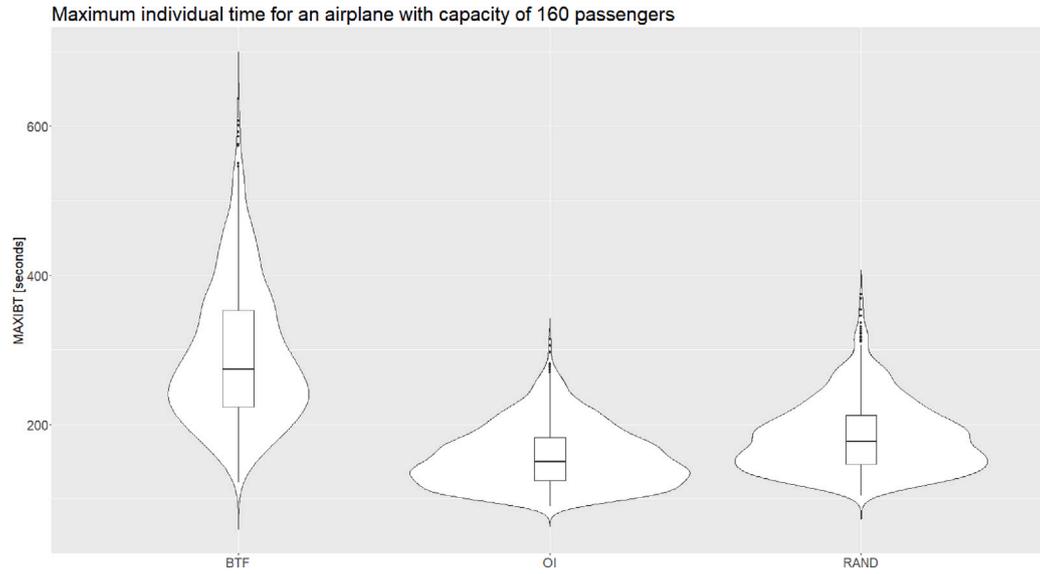


Fig. A.18. Maximum Individual Boarding Time (MAXIBT) in terms of boarding strategy (STRATEGY) for a 160-seat passenger airplane (RAND = random, BTF = back-to-front, OI = outside-in).

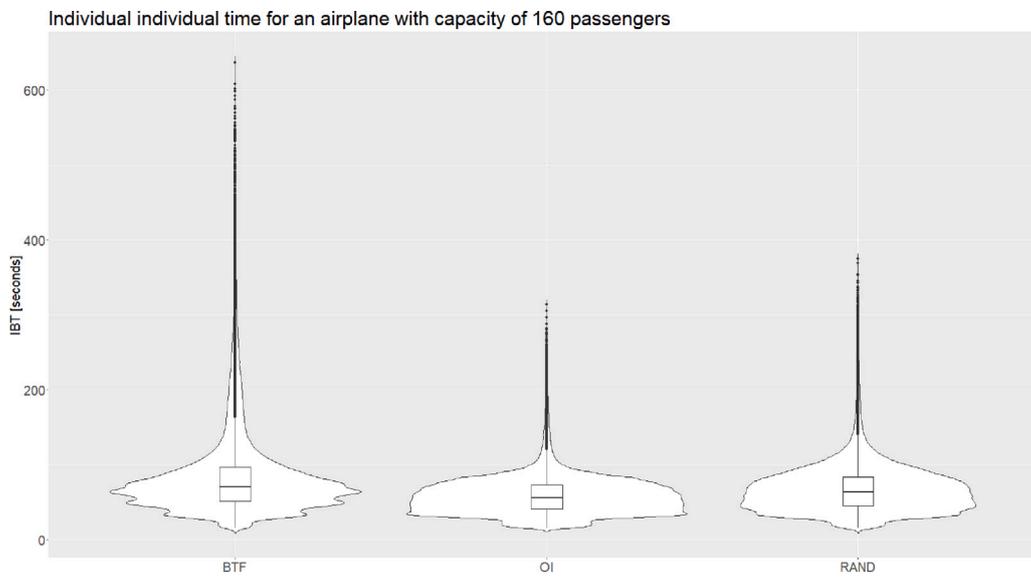


Fig. A.19. Individual Boarding Times (IBT) in terms of boarding strategy (STRATEGY) for a 160-seat passenger airplane (RAND = random, BTF = back-to-front, OI = outside-in).

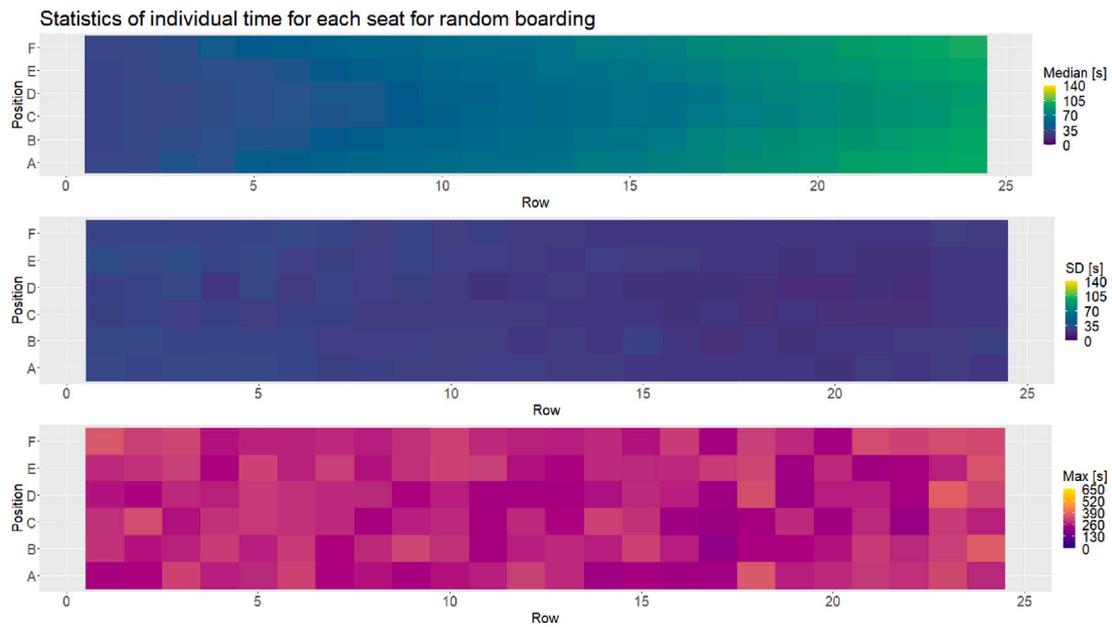


Fig. A.20. Individual Boarding Times (IBT) in seconds per seat for random boarding on a 160-seat passenger airplane.

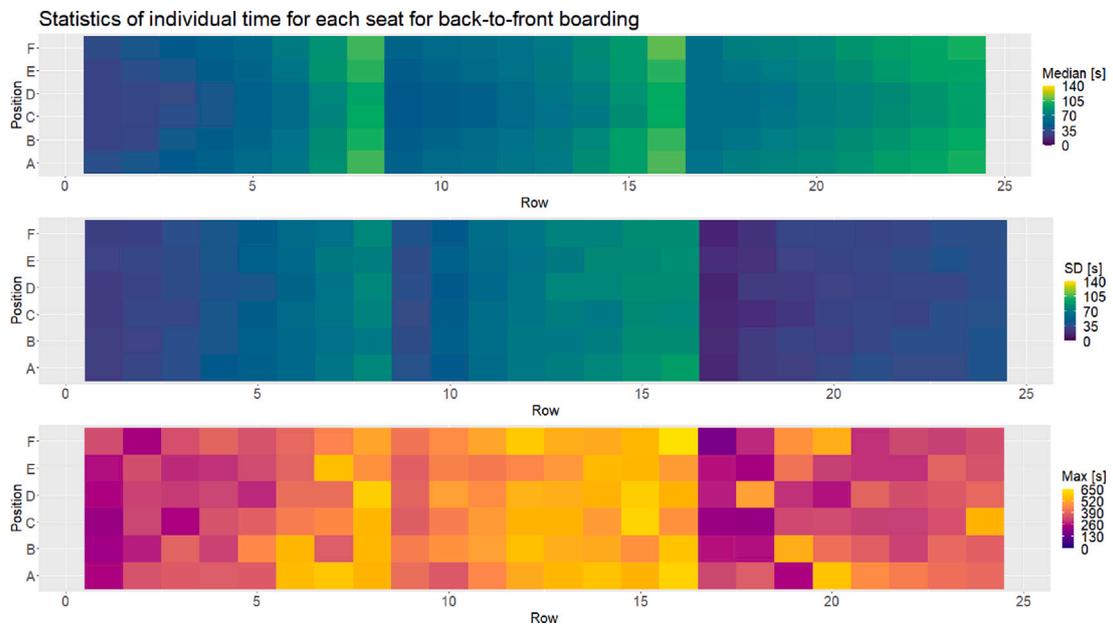


Fig. A.21. Individual Boarding Times (IBT) in seconds per seat for back-to-front boarding on a 160-seat passenger airplane.

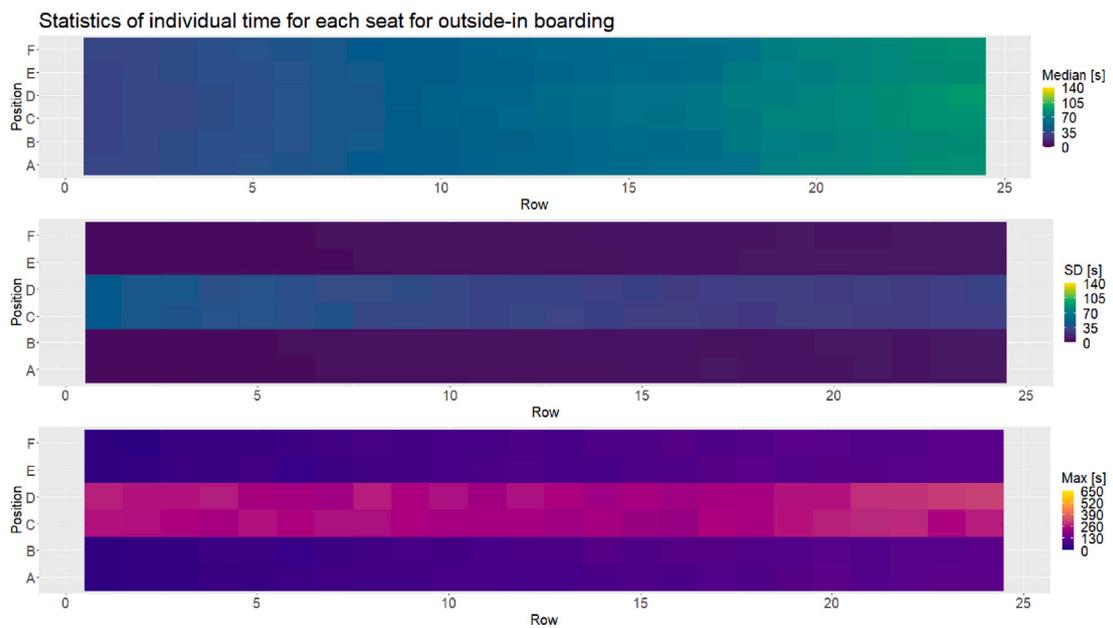


Fig. A.22. Individual Boarding Times (IBT) in seconds per seat for outside-in boarding on a 160-seat passenger airplane.

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