Look-Ahead Airline Seat Allocation: Enhancing Efficiency in Passenger Transfers at Hub airports

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***Abstract*—This study examines the effect of seat assignment strategies on the transfer time of connecting passengers at a hub airport. Passenger seat allocation significantly influences disembarkation times, which can increase the risk of missed connections, particularly in tight transfer situations. We propose a novel seat assignment strategy that allocates seats to non-paying passengers after check-in, prioritising those with tight connections. This approach diverges from traditional methods focused on airline turnaround efficiency, instead optimizing for passenger transfer times and reducing missed connections. Our simulation, based on real-world data from Paris-Charles de Gaulle airport, demonstrates that this passenger-centric model decreases missed connections by 12%, enhances service levels, reduces airline compensation costs, and improves airport operations. The model accounts for variables such as seat occupancy, luggage, and passenger type (e.g., business, leisure) and is tested under various scenarios, including air traffic delays.**

***Keywords*—Airline seat allocation, Simulation, Connecting passengers, Aircraft disembarkation**

I. Introduction

The COVID-19 pandemic deeply impacted the airline industry, leading to a resurgence of the hub-and-spoke strategy [1]. This change has increased the number of connecting flights offered by airlines to passengers. While this strategy allows airlines to cover a wider range of destinations, it also introduces greater uncertainty into passenger journeys. A delay on the first flight can lead to missed connections, resulting in significant delays at the final destination.

Missing a connecting flight is often the result of a series of interrelated events: a delay on the first flight, a long taxiing time on arrival, a long disembarkation time, long walking distances due to distant disembarkation and boarding gates, or long queues at border control for international flights. These factors can result in passengers arriving late at their departure gate and being stranded.

This scenario is highly undesirable for passengers, who must then wait to be re-accommodated on another flight. However, it is equally problematic for airlines. According to Regulation (EC) No 261/2004 [2], airlines must re-book passengers who miss their connections, and if the delay exceeds three hours, as is often the case when a connection is missed, they must also provide financial compensation.

The literature has explored various methods to improve passenger transfers. For example, Kim *et al.* [3] investigated gate assignment optimization as a way to balance the needs of airports and airlines. However, this approach is challenging to implement due to the complexity of gate allocation, which involves numerous factors such as airport management strategies, taxiway logistics, gate conflicts, aircraft compatibility, and strategic decisions about passenger flows and even shopping behaviour.

Guo *et al.* [4] used a combination of regression trees and simulations to predict passenger flow at immigration and transfer security areas. Their approach allows airports to anticipate late-arriving passengers and assist them in catching their connecting flights by speeding up transfers or early re-booking. However, their study does not clearly outline specific actions, such as reallocating security staff to handle delayed passengers, nor does it address the costs associated with these decisions. While re-booking helps passengers, it does not prevent delays at their final destination.

An important area for improvement is the optimisation of the disembarkation process. Wald *et al.* [5] and Qiang *et al.* [6] have shown that structured disembarkation strategies outperform unstructured ones. In particular, column-based strategies, in which passengers disembark from left to right or from the aisle to the window, tend to reduce total disembarkation time more effectively than traditional front-to-back row-based methods. While these studies evaluate metrics such as total or average passenger disembarkation time, they do not address the specific needs of connecting passengers and focus solely on overall disembarkation efficiency.

This study focuses on a related but distinct issue: seat allocation strategy. The seat assigned to a passenger plays a crucial role in determining his or her disembarkation time, which has a direct impact on transfer times for connecting passengers. We propose a novel seat assignment strategy that prioritises passengers with tight connections, moving away from the current practice of randomly assigning seats to passengers who do not pay for seat selection. By recognising the additional stress and time pressure faced by passengers with shorter transfer windows, we aim to allocate seats in a way that minimises their disembarkation time, thereby reducing the likelihood of missed connections and improving the overall passenger experience.

This approach involves a minor adjustment to the check-in process. Passengers willing to pay an additional fee can still select a specific seat. Those who opt not to pay will check in without an assigned seat. At the close of the check-in period, airlines will allocate the remaining seats based on priority, considering expected connection times. This strategy assumes that airlines possess information about connecting passengers, which is typically available for those travelling within the same airline or alliance.

The proposed seat allocation strategy is evaluated using a cellular automata simulation model inspired by Schultz *et al.* [7]. Although simple, this model can be fine-tuned to realistically simulate passenger behaviour. The case study is on Paris-Charles de Gaulle airport, using historical flight schedules and actual gate delay data. Passenger flows are simulated and a connecting passenger scheme is generated across the airport based on a day of historical operations. Simulations are performed, incorporating stochastic elements such as luggage collecting time or pre-reserved seat selection. The results are compared with those from the traditional random seat allocation to assess the benefits of the proposed seat allocation strategy. To promote open science, all code used to generate this research is publicly available at the following link: https://github.com/geoffreyscozzaro31/planeDeboarding.

The remainder of the paper is structured as follows. The modelling framework is described in Section II. Section III presents the seat allocation strategy and Section IV the disembarkation simulation validation. The case study is introduced in Section V. Finally, Section VI presents the results.

II. Modelling Framework

This section outlines the modelling framework adopted for the aircraft disembarkation process.

A. Simulating disembarkation process

We use a simulation-based approach to model the passenger disembarkation process. This method effectively captures passenger interactions and provides a realistic evaluation of airport operations such as boarding procedures [8] and security screening systems [9].

Our model is inspired by the work of Schultz *et al.* [7] and uses cellular automata to simulate the disembarkation process. In this model, the aircraft is divided into square cells, each of finite size and capable of accommodating a single passenger. These cells represent either a seat or a section of the aircraft aisle. In this work, we adopt the following assumptions:

1) aircraft considered in this study are typical of medium-range configurations, such as the A320 or B737, which feature a single aisle with a 3+3 seating arrangement,
2) disembarkation occurs exclusively through the front door.

Each passenger is assigned a dynamic status, among the following ones: "seated", "standing up from the seat", "moving in the aisle", "waiting in the aisle", "collecting luggage", and "disembarked".

Passenger movement is modelled using a cellular automata approach, where the evolution of passengers' positions occurs in discrete time steps according to predefined rules. At the start, all passengers are in the "seated" status. As flights may not be fully booked, some seats remain unoccupied. During each time step, passengers who can reduce their distance to the exit by moving to an adjacent available cell will do so. Three types of actions are considered:

1) Moving left/right: Passengers still seated may move to an adjacent cell (either a seat or the aisle) if it is vacant.
2) Moving forward: Passengers in the aisle may move forward, if the next cell is empty, to proceed to the exit.
3) Collect luggage: Passengers with baggage will collect it from the overhead bin directly above their row. They will remain in the corridor cell for a specified time to collect their luggage.

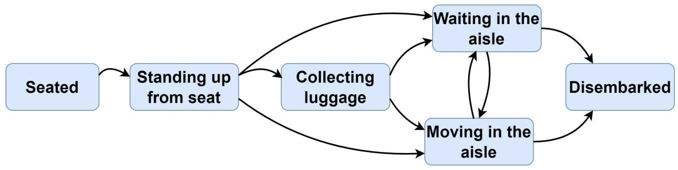


Figure 1. Passenger status transition flow. Each case represents a passenger status, and each arrow represents a possible status transition.

Figure 1 illustrates the passenger status transition flows during the disembarkation process.

B. Conflict resolution strategies

When two passengers from adjacent cells attempt to enter the same empty cell, a conflict arises. Two main rules are introduced to deal with this:

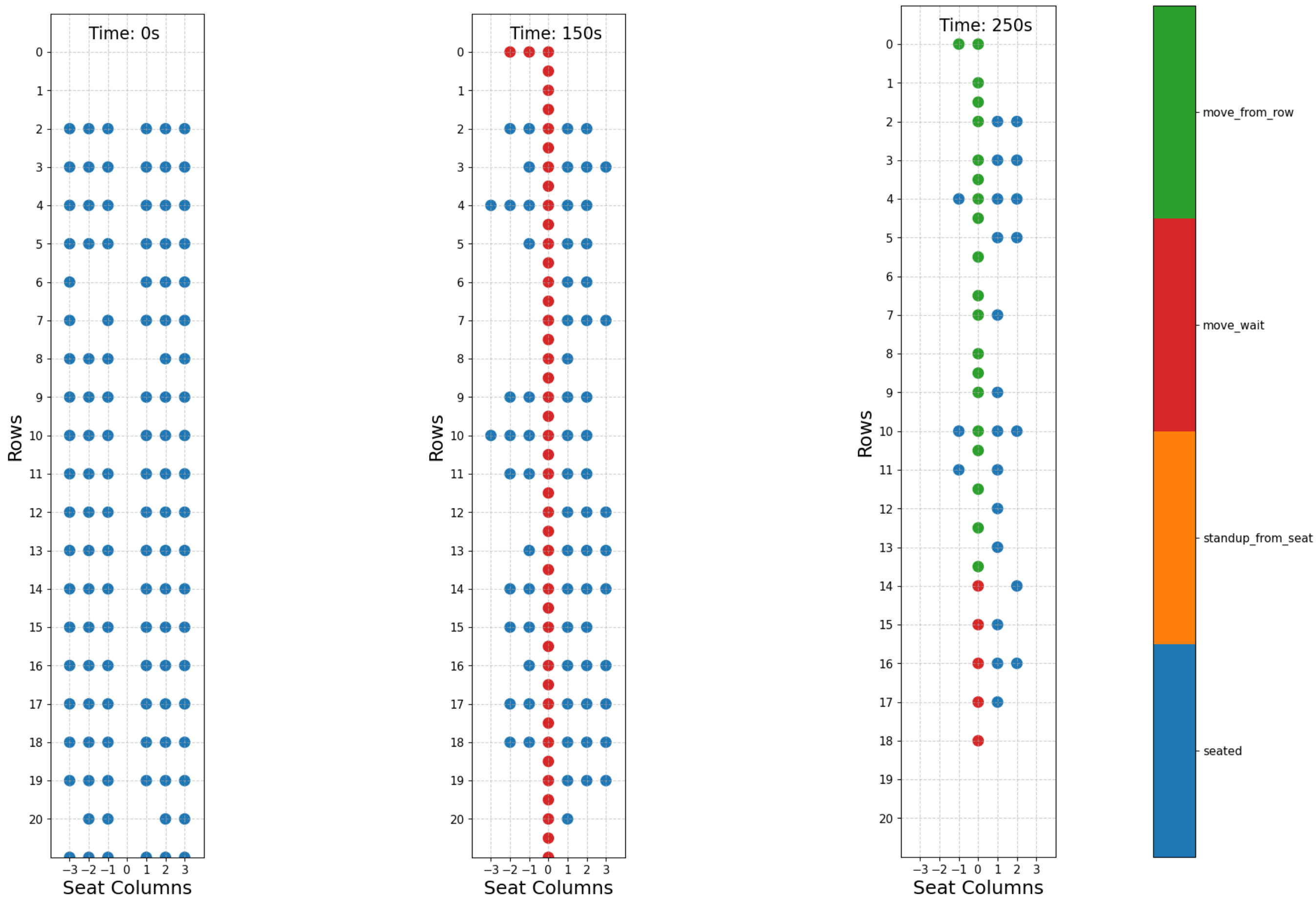
- *Courtesy Rule:* This strategy prioritises passengers closer to the exit, giving precedence to those in the front rows over those in subsequent rows. If passengers from both the left and right attempt to enter the aisle simultaneously, a random selection determines who moves first.
- *Aisle-priority rule:* This strategy always gives priority to the passenger already in the aisle, ensuring that their movement towards the exit takes precedence over those still seated or moving from adjacent cells.

This model accounts for the time required for each passenger action, allowing different speeds to be assigned to various movements. For example, the luggage retrieval process is simulated by a brief pause after the passenger stands in the aisle.

The different movement speeds are represented by the time spent in each cell. The simulation is divided into identical time steps, and the step duration is calibrated to the shortest allowed movement duration.

Additionally, a buffer time is included to account for the deployment of the jet bridge before the gate opens. The different parameter settings used to configure the simulation are thoroughly described and validated in Section IV.

Figure 2 presents a visualisation of the disembarkation process, following the *aisle-priority rule*, at three different time steps. The GIF animation is available through the following link: https://github.com/geoffreyscozzaro31/planeDeboarding/blob/main/medias/deboarding/animations/animation_deboarding_aisle_priority_deboarding_rule_45fps_v2.gif



(a) Frame 0/642 (b) Frame 300/642 (c) Frame 500/642

Figure 2. Screenshots of the disembarkation process simulation at different time steps. In this scenario, disembarkation priority is given to passengers already in the aisle.

III. Seat Allocation Strategy

We propose a novel seat allocation strategy for passengers who have checked in without pre-booking their seats. Airlines can implement this allocation after the check-in deadline, once the total number of unallocated passengers is known. The strategy aims to minimise the risk of connecting passengers missing their next flight by prioritising them based on their estimated transfer time - a value that airlines can usually calculate using available data on passengers connecting to other flights within the same alliance.

Each passenger is assigned a priority index, P_i, where i is the passenger index, based on the urgency of their connection. The passengers are then ordered such that $P_1 > P_2 > \cdots > P_N$, where N represents the total number of passengers still awaiting seat assignments.

The seat assignment process can be formulated as a matching algorithm. Let S_j denote the availability of the j-th seat, where $S_j = 1$ if the seat is available and $S_j = 0$ otherwise. Each seat S_j is associated with a disembarkation time T_j, where $T_1 < T_2 < \cdots < T_M$ represents the disembarkation time for all M seats, ranked in ascending order. The goal of the matching algorithm is to assign the highest-priority passenger to the seat with the earliest disembarkation time.

Here is the pseudo-code of the seat allocation strategy:

Passenger-Seat matching algorithm

1) **Variable Definitions:**
   - S_j **= 1 if the** j**-th seat is already booked, 0 else**
   - P_i **= Priority index of passenger** i
   - T_j **= Disembarkation time for seat** j
2) **Sort passengers by descending priority index:**
   - $P_1 > P_2 > \cdots > P_N$
3) **Sort seats by ascending disembarkation time:**
   - $T_1 < T_2 < \cdots < T_M$
4) **Initialize indices:**
   - $i \leftarrow 1$ **(Passenger index)**
   - $j \leftarrow 1$ **(Seat index)**
5) **While** $i \leq N$ **and** $j \leq M$ **do:**
   - **if** S_j **= 0:**
     - **Assign passenger** i **to seat** j
     - $i \leftarrow i + 1$
   - $j \leftarrow j + 1$

Parameter	Value
Cell size	0.4mx0.4m
Cell capacity	1 passenger
Number of rows	n
Seat per row	3 +3
Number of cells	n*6*2
Simulation's time step	0.5s
Moving left/right/forward	0.5s
Luggage collecting duration	$X \sim Weibull(\alpha = 1.7, \beta = 8)$
Jet bridge deployment time	180s

TABLE I. SIMULATION PARAMETERS

The disembarkation time T_j for each seat is determined by the disembarkation strategy used, such as the *courtesy rule* or the *aisle-priority rule* presented in Section II. For example, if passengers are disembarking under the *courtesy rule*, rows will empty sequentially from the front to the back of the aircraft. In this case, seats in the first row will have shorter disembarkation times than those in subsequent rows. On the other hand, if the *aisle-priority rule* is applied, seats closer to the aisle will have shorter disembarkation times. This means, for example, that a passenger in the third row, seated close to the aisle, should disembark before a passenger seated by the window in the first row.

Exceptions may occur when passengers retrieve luggage from the overhead bins, potentially blocking those behind them and allowing passengers in the rows ahead to disembark earlier under the *aisle-priority rule*. A similar situation may arise under the *courtesy rule* if there are empty seats in a row, allowing a passenger sitting in an aisle seat in a rear row to disembark before a passenger sitting further forward.

For simplicity, we disregard these exceptions and assume that passengers seated closer to the aisle will disembark earlier under the *aisle-priority rule*. Conversely, passengers in the front rows will disembark earlier under the *courtesy rule*.

The performance of the proposed seat allocation strategy is compared to the traditional random assignment method through multiple simulations. Different key performance indicators are assessed, such as passenger disembarkation times, or the number of passengers missing their connections. The details and parameter values used for calibration and simulation are provided in the following section.

IV. SIMULATION

We calibrate our simulation using various parameters inspired by [7], which are summarised in Table I. The disembarkation model developed in this paper is verified by comparing its results with findings from the existing literature. Namilae *et al.* [10] provided reference values for similar aircraft configurations, specifically single-aisle aircraft with 3+3 seats per row. Their study reported disembarkation times of 8 to 10 minutes for a 144-seat configuration and 10 to 12 minutes for an 182-seat configuration, using the *courtesy rule* disembarkation strategy (*i.e.* from the front to the rear of the aircraft).

To maintain consistency with the reference study, this analysis assumes that the aircraft was operating at 100% load factor, with all passengers carrying overhead luggage. Gate bridge connection time was excluded. For each configuration (144 seats and 182 seats), 100 replications of the simulation experiment were performed to account for the stochasticity of baggage collection times. Among the 100 replications, the minimum, average and maximum total disembarkation time are extracted. Table II summarises the simulation results for both the *courtesy rule* and the *aisle-priority rule* followed during passenger disembarkation.

TABLE II. TOTAL DISEMBARKATION TIMES (IN MINUTES) OVER 100 SIMULATIONS DEPENDING ON DISEMBARKATION STRATEGY

Cabin config	Courtesy rule			Aisle-priority rule		
	Min	Mean	Max	Min	Mean	Max
144-seat	7.60	9.42	11.29	5.16	6.47	7.76
182-seat	10.02	11.92	14.12	6.57	8.12	9.60

This table shows that the model produces results under the *courtesy rule* for passenger disembarkation comparable to those in the literature. The average disembarkation times are centred on the expected range, *i.e.* 8-10 minutes for the 144-seat configuration and 10-12 minutes for the 182-seat configuration, with slightly larger minimum and maximum values. This consistency underscores the model's robustness, as it aligns well with established findings and effectively simulates the disembarkation process.

The *aisle-priority rule* was also evaluated to determine whether it reduces the total disembarkation time, as expected, according to [5] and [6]. The results in Table II show a clear reduction in time compared to the *courtesy rule*, further increasing confidence in the simulation model. These findings support the subsequent analyses in Section VI, which assess the impact of seat allocation on connecting passenger transfers.

V. CASE STUDY

This section details the methodology we developed for modelling passenger transfers at Paris Charles de Gaulle (CDG) airport, using historical flight and passenger data. First, the parameters for flight disembarkation are introduced. Next, the methodology for simulating connecting passengers is outlined. Finally, the operational characteristics of the historical operating day considered, including arrival and departure flight sets, are described.

A. Flight disembarkation

The simulation of the disembarkation process is based on a single-aisle medium-haul aircraft with a typical 3+3 seating configuration. The number of rows varies according to the flight selected. Only medium-range arriving flights are analysed, excluding long-range twin-aisle aircraft. Passengers are divided into three groups: (1) those with pre-booked seats, (2) transfer passengers without pre-booked seats and (3) all other passengers. Business class passengers are assumed to have pre-booked seats.

We assume the following distribution of passenger types 20% with pre-booked seats, 40% as transfer passengers with-

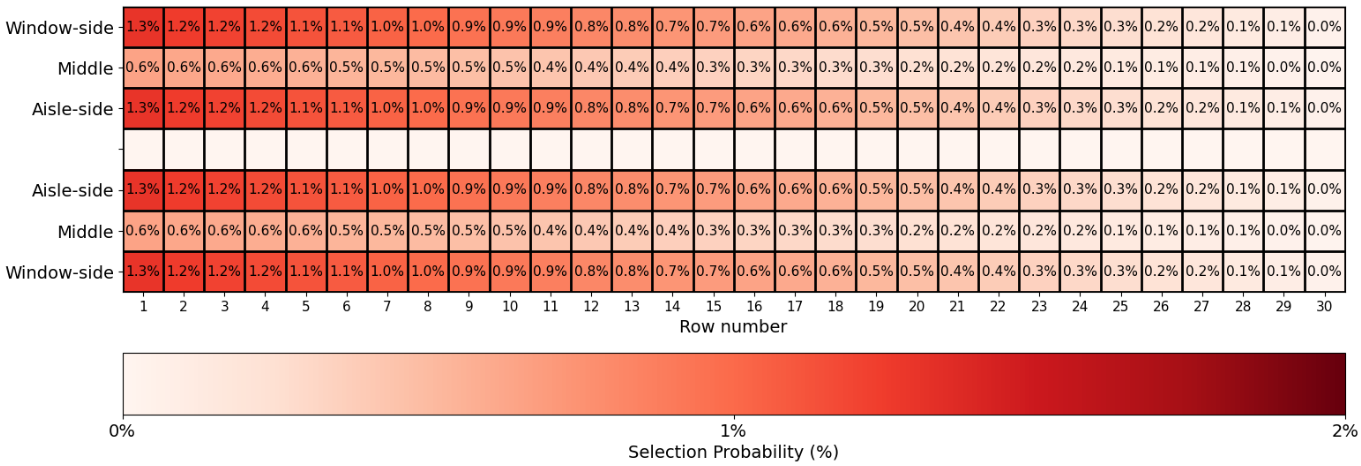


Figure 3. Probability distribution of pre-booked seat selection for a 30-row aircraft. Row 1 is positioned at the front of the cabin.

TABLE III. PARAMETERS FOR FLIGHT DISEMBARKING SIMULATION

Parameter	Value
% of passengers with pre-booked seats	$X \sim \mathcal{U}(15\%, 25\%)$
% of connecting passengers	$X \sim \mathcal{U}(30\%, 50\%)$
% Other passengers	Adjusted to sum to 100%
% Passengers with carry-on luggage	$X \sim \mathcal{U}(85\%, 95\%)$
% Aircraft seat occupancy	$X \sim \mathcal{U}(81.5\%, 91.5\%)$

out pre-booked seats, and 40% categorised as other. To introduce variability, we apply a uniform random value of $\pm 5\%$ to the proportions of pre-reserved seats, and a uniform random value of $\pm 10\%$ for the share of transfer passengers.

In terms of the location of pre-reserved seats, Shao *et al.* [11] found that passengers have a strong preference for seats at the front of the aircraft and tend to avoid middle seats. Consequently, we design a probability distribution that favours the allocation of pre-booked seats to the front of the aircraft, and specifically to window or aisle seats. Figure 3 illustrates the probability distribution we retain on an example for a 30-row aircraft.

Regarding cabin baggage, the proportion of passengers carrying cabin baggage varies across airlines. Low-cost carriers typically charge extra for cabin baggage, reducing its prevalence among passengers. However, since this study focuses on major airlines operating at CDG that offer free cabin baggage, we assume that 90% of passengers have cabin baggage, with a random variation of $\pm 5\%$.

Seat occupancy is defined based on Air France's June 2019 activity report (https://www.airfranceklm.com/sites/default/files/communiques_en/document/trafic_jun19_va_vdef.pdf), which reports an average passenger load factor of 86.5% for short- and medium-haul flights. We adopt this value and apply a uniform random variation of $\pm 5\%$. Table III summarises the parameters retained for simulating flight disembarkation.

B. Passenger transfer modelling

Since the dataset does not include information on the number of transfer passengers per flight, a modelling framework was developed to generate connecting passengers. A specific proportion of transfer passengers and a realistic transfer time window are considered to identify potential connecting flights. A focus is made on flights operated by the airport's main airline, as connecting flights are typically managed by the same airline or by airlines within the same alliance. Due to the absence of gate assignment data for each flight, the average transfer time cannot be directly calculated. Instead, a transfer time is randomly selected from a predefined interval to represent the minimum required transfer time. Additionally, a boarding threshold before departure is also considered.

According to the Paris Aéroport website (https://www.parisaeroport.fr/passagers/les-vols/temps-entre-deux-vols), the minimum transfer time ranges from 10 to 95 minutes. This range is used to generate realistic walking transfer times for connecting passengers. In addition, we allow a minimum buffer of 10 minutes between the walking time and the scheduled transfer time to avoid generating infeasible transfers, in line with common industry practice where airlines avoid creating impractical transfer schedules.

We assume that, on average, 40% of passengers on each flight are connecting passengers, and consider a random variation uniformly distributed between [-10%, 10%].

Air France, one of the main airlines operating at CDG, states that the boarding time is between 15 and 20 minutes, depending on whether the flight is domestic or international (https://wwws.airfrance.fr/en/information/aeroport/quand-arriver). For this study, 20 minutes is used as no distinction is made between domestic and international flights.

A potential connection is defined as two flights, one arriving and one departing, with a reasonable transfer time for passengers, falling within the following time window:

- Minimum transfer time: 45 minutes.
- Maximum transfer time: 3 hours.

These thresholds ensure that only practical connections are considered. For each arriving flight, the model identifies potential departing flights within the specified transfer time window. Connecting passengers are then randomly assigned to these

TABLE IV. CHARACTERISTICS OF THE OPERATIONAL DAY CONSIDERED

Date	2019-06-24
Number of arriving flights	726
Number of departing flights	721
Total number of arriving passengers	121854
Total number of departing passengers	124579
Average delay per arriving flight	8.14 minutes
Average delay per departing flight	20.76 minutes
Number of arrivals operated by the considered airline with fewer than 200 passengers	275
Number of connecting passengers simulated	13698

flights, ensuring a realistic distribution across the available connections.

In this study, we focus exclusively on departures from single-aisle aircraft and connecting passengers within the same airline. Therefore, we only consider arrival flights carrying less than 200 passengers and operated by the main airline operating at CDG airport. In the absence of exact aircraft configurations, we estimate the number of rows based on the passenger load factor for each instance. For example, if 180 passengers were carried and the passenger load factor is set to 90%, the total number of seats is calculated as follows:

$$\left\lceil \frac{180}{0.9 \times 6} \right\rceil = 34 \text{ rows}$$

C. Characteristics of the historical operating day considered

We consider one day amount the data set that covered one month of historical traffic at CDG airport. This day was the busiest day in June 2019, with a total of 1447 flights operated during the day. The different characteristics of this day are presented in Table IV.

Both theoretical and actual transfer times are calculated for each generated connection:

- **Theoretical transfer time:** The difference between the scheduled arrival and departure times of the flights used to identify candidate connections. This time is considered when allocating seats to connecting passengers.
- **Actual transfer time:** The difference between the actual block times of the flights, taking into account any operational delays. This time is considered to assess, after simulating the disembarkation time, whether passengers will be able to make their connections.

Figure 4 illustrates the distribution of transfer times for the selected day. The data show that delays contributed to a broader dispersion of transfer times, with arrival delays increasing the pressure on passenger transfers, while departure delays extended the overall transfer duration. Several connections became infeasible due to delays, resulting in some instances of negative transfer times.

VI. RESULTS AND DISCUSSION

This section presents the results of the case study outlined earlier. We simulated the disembarkation process for all flights with fewer than 200 passengers over a whole day of operations, evaluating passenger disembarkation times. To account for stochastic factors such as the proportion of passengers

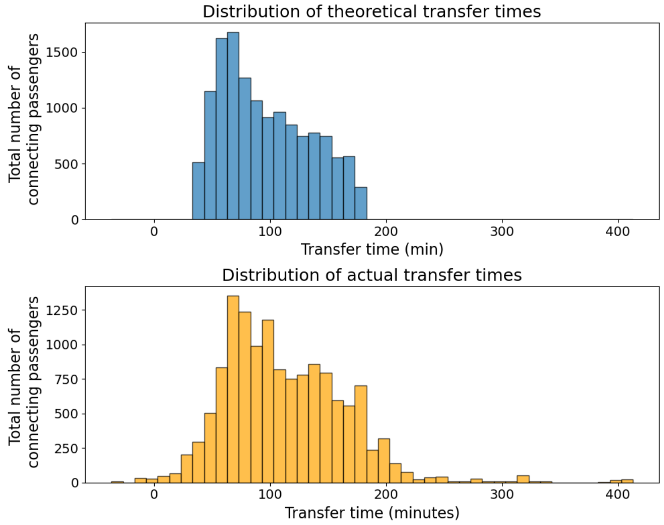


Figure 4. Passenger transfer time distribution for the historical operating day. Scheduled and actual transfer times are represented by blue and orange curves, respectively.

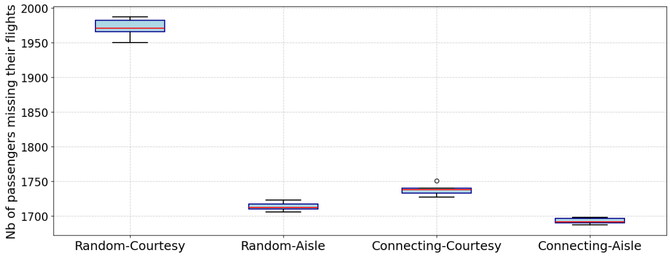
with hand luggage, luggage retrieval time, the number and distribution of pre-assigned seats, and other variables, we conducted 10 simulations for the whole day.

A. Seat allocation strategies: Random vs. Connecting passenger priority

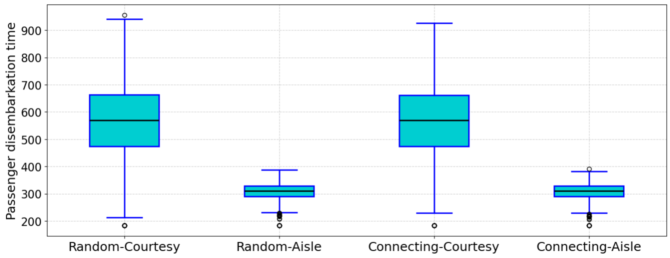
The study aimed to compare two seat allocation strategies for non-reserved seats: a random allocation method and a proposed strategy that assigns seats to passengers with tight transfer times to minimise disembarkation duration. This comparison was conducted under two disembarkation protocols: the *courtesy rule*, where passengers in front rows disembark first, and the *aisle-priority rule*, which prioritises passengers seated closest to the aisle.

A total of 4x10 simulations were conducted to evaluate the outcomes for an entire day of operations. Figure 5a and 5b present box plots illustrating the total number of passengers missing their flights and the average disembarkation times, respectively. Each box plot corresponds to a specific combination of seat allocation strategy for unreserved seats and the disembarkation rule applied. For the x-axis, "random" refers to a random seat allocation, while "connecting" refers to an allocation focused on connecting passengers. Similarly, "courtesy" and "aisle" refer to the *courtesy rule* and the *aisle-priority rule* used for disembarkation, respectively.

The "Random-Courtesy" box plot of Figure 5a, which represents the random seat allocation strategy combined with the courtesy disembarkation rule, translates the worst performance, with 1,950 to 1,990 passengers missing their connections over the day. In contrast, the same seat assignment combined with the *aisle-priority rule* for disembarkation enables approximately 250 additional passengers to make their connections (cf "Random-Aisle" box plot). This improvement is attributed to the significant reduction in overall disembarkation time under the *aisle-priority rule*, as demonstrated through



(a) Number of passengers who missed their connecting flight during the day



(b) Passenger disembarkation times throughout the day

Figure 5. Box plots illustrating the total number of passengers missing their connecting flights (top figure) and passenger disembarkation times (bottom figure) across the operating day. Each box plot represents the results from 10 simulation runs, with each box corresponding to a unique combination of seat allocation strategy and disembarkation rule.

Figure 5b. Specifically, the average disembarkation time is reduced by 45%, from 9 minutes to 5 minutes. This reduction is crucial for passengers with tight connections, allowing about 13% more of them to successfully catch their onward flights.

Equally remarkable is the impact of the new seat allocation strategy proposed in this study compared to the traditional random allocation. This can be done by comparing the "Random-Courtesy" box plot with the "Connecting-Courtesy" one of Figure 5a. The new allocation leads to a 12% reduction in the number of passengers missing their flights. This effect is almost equivalent to that obtained by changing the disembarkation rule, although it does not affect the disembarkation times, as observed in Figure 5b by comparing the "Random-Courtesy" and "Connecting-Courtesy" box plots.

By combining the benefits of a connecting passenger-oriented seat allocation strategy with the *aisle-priority rule* for disembarkation, the total number of passengers missing their flights is reduced to less than 1,700 (cf "Connecting-Aisle" box plot Figure 5a). This represents an overall reduction of 14% compared to the traditional strategy used by airlines, *i.e.* random seat allocation and the *courtesy rule* for disembarkation. However, the savings from the two strategies are not cumulative, *i.e.* the improvement is lower than 13% + 12%, since if disembarkation times are already minimised, the seat reassignment of connecting passengers is less effective in helping them to make their connections.

From a practical perspective, seat reassignment is easier to implement than disembarkation strategies, which require passenger coordination. In particular, *aisle-priority rule* requires the active involvement of staff, making it less practical. In contrast, seat reallocation can be integrated into the pre-boarding process without requiring real-time intervention.

The observed reduction in the number of passengers missing their flights represents a significant improvement in both passenger experience and airline cost management. Indeed, a missed connection can lead to significant delays for passengers at their final destination. Bratu *et al.* [12] estimate that if stranded passengers represent only 3% of the total delayed passenger volume, their delays represent 39% of the total passenger delay, *i.e.* a total delay at their final destination of 303 minutes. This result is also beneficial for airlines, as re-accommodating passengers who miss their connections involves both logistical and financial costs. European Union Regulation (EC) No 261/2004 requires airlines to compensate passengers for missed connections and long delays. In addition, missed connections can degrade passengers' perception of the airline, leading to reduced customer loyalty and erosion of market share. This effect, as highlighted by Cook *et al.* [13], can be a dominant factor in the economics of airline delays. The proposed seat allocation strategy creates therefore a win-win situation for both airlines and passengers.

B. *Influence of the percentage of pre-reserved seats*

The influence of the proportion of pre-reserved seats on the performance of the seat allocation strategy proposed in this paper is evaluated below. The results presented earlier were based on the assumption that approximately 20% of seats were pre-reserved. Here, we ran simulations with pre-reservation rates ranging from 0% to 100% over the day. The 0% scenario, although hypothetical, represents a case where no seats are pre-reserved, allowing the seat allocation algorithm full flexibility to assign optimal seats to passengers with tight connections. In contrast, the 100% pre-reserved scenario reflects a random seat allocation where all seats are already pre-reserved and the seat allocation algorithm is inactive. The only difference is that it assumes a slightly higher probability that passengers will choose front, aisle or window seats, resulting in a higher probability that middle and rear seats will remain unoccupied. For this analysis, we will focus only on the courtesy disembarkation rule, as it is the traditional rule adopted in operational conditions. Figure 6 illustrates the impact of the proportion of pre-reserved seats on the number of passengers missing their connecting flights.

The key observation is that the lower the percentage of pre-reserved seats, the more effective the connecting passenger seat reallocation strategy becomes. This is because pre-reserved seats tend to be those with shorter disembarkation times, such as those at the front of the aircraft or near the aisle. A high proportion of pre-reserved seats limits the ability of the algorithm to optimally allocate seats with shorter disembarkation times to connecting passengers with tight transfer windows. The increase in efficiency follows a linear trend, with 2,000 passengers missing their flights with 100% pre-reserved seats to 1,700 with 0% pre-reserved seats. This represents an improvement of 15%.

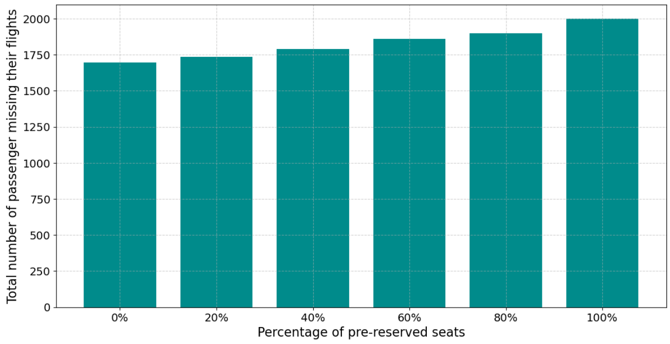


Figure 6. Evolution of the number of passengers missing their flights as a function of the proportion of pre-reserved seats. The 100% pre-reserved strategy mirrors random seat allocation, where connecting passengers are randomly distributed throughout the cabin. The courtesy disembarkation rule, *i.e.* passengers disembarking from front to rear, is considered here.

VII. Conclusion

This study investigates the potential benefits of an innovative look-ahead seat allocation strategy that prioritises connecting passengers, yielding advantages for passengers, airlines, and airports. Unlike the traditional random allocation of unreserved seats, which primarily benefits airlines, our approach assigns seats with shorter disembarkation times to passengers with tight connections. We tested this strategy using real data from Paris Charles de Gaulle Airport, focusing on small- and medium-sized aircraft operated by a major airline. The analysis incorporated actual flight delays, further constraining passenger transfer times compared to scheduled connections. The results indicate that, under a front-to-rear disembarkation strategy with a single front exit, the proposed seat allocation for non-reserved seats enables approximately 12% of passengers to successfully recover their initially missed connections.

The proportion of pre-reserved seats plays a critical role in the effectiveness of the proposed seat allocation strategy. A higher percentage of pre-reserved seats reduces the algorithm's efficiency, as most seats with short disembarkation times are already reserved. This underscores the potential advantage for airlines that offer paid seat reservations, as limiting the number of pre-reserved seats may increase the benefits of this reallocation strategy up to 15%.

Overall, the proposed seat reallocation strategy offers a win-win solution for airlines, passengers, and airports. Additionally, it helps reduce the costs airlines incur in re-accommodating and compensating passengers as mandated by Regulation (EC) No 261/2004.

Future work could incorporate detailed data on connecting passengers, origin-destination pairs, gate assignments, and terminal configurations for a more accurate assessment of transfer times. The framework's flexibility allows for the integration of more complex data. Additionally, it currently overlooks the behaviour of passenger groups, which strongly influences passenger speed [14] and should therefore be considered in future studies. Including such behaviour in future iterations would improve the accuracy of the seat allocation strategy.

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