CSC446 GROUP PROJECT

Alberto Yanes V00895987
Eric Showers V00799842
Viet Ngo V00970886

“An aircraft onboarding process simulator”

April 11, 2023

Table of Contents

Introduction

In this report, we will discuss a simulation project focused on the process of boarding passengers onto an airplane. Specifically, we will compare and contrast the effects of different methods of ordering passengers as they queue outside the plane. The goal of this simulation is to create a realistic representation of the boarding process to understand how it can be optimized for both maximum efficiency and customer satisfaction. Through this project, we aim to improve the overall travel experience for passengers and lower the operating costs of commercial airlines.

Simulation Model

Goals

The goal of this simulation is to analyze the total duration and passenger comfort of the boarding process. The first metric is easily defined as the time required to load all passengers onto the plane. For commercial airlines, it is important to optimize time so that each airplane may complete more flights, thereby increasing revenue. The second metric, passenger comfort, is measured by both the average (a) time passengers spend standing on the plane, and (b) number of passengers standing on the plane at any one time. Passengers may find it uncomfortable to stand on an airplane for long durations when they could be sitting inside the airport instead while waiting to board. Similarly, passengers may find it uncomfortable to stand in an airplane when the aisle is completely full. Through an experimental analysis of our simulations, we aim to determine the best methods of ordering passengers in order to optimize efficiency and comfort throughout the boarding process.

Parameters

To simulate the boarding process, we will vary two key parameters: the size of the aircraft and the ordering of passengers. The three plane sizes that we will analyze are based on typical commercial aircraft used for domestic and international flights in Canada. Aircraft sizes vary according to seat rows and seat columns on either side of the aisle, and are categorized as small, medium, or large (see Table 1).

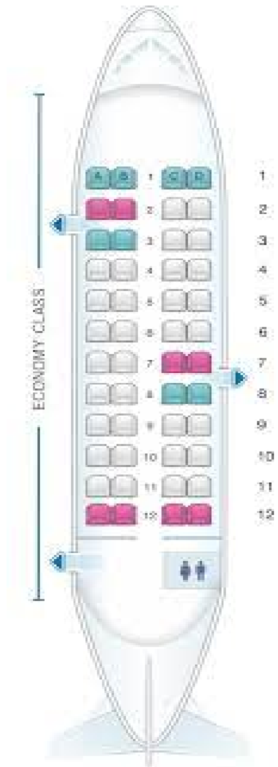
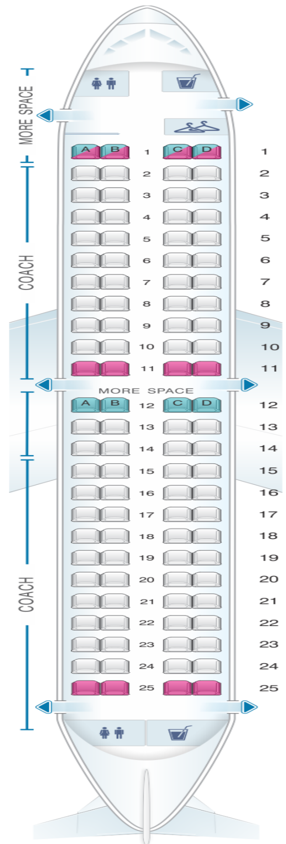
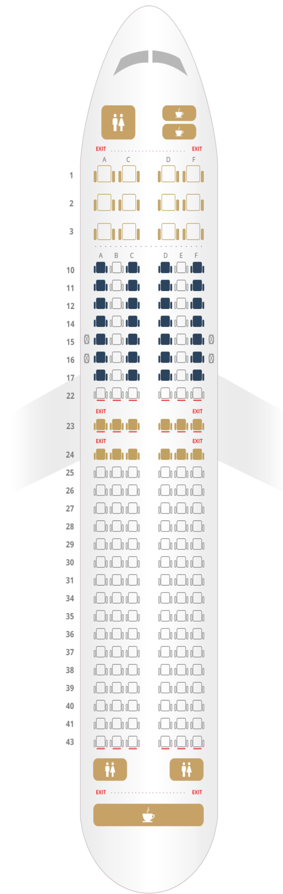
Size	Small	Medium	Large
Aircraft	Antonov An-24	Embraer e-jet Family	Boeing 737
Rows	12	25	43
Seats Per Row	4 (2, 2)	4 (2, 2)	6 (3, 3)
Images	 Figure 1	 Figure 2	 Figure 3

Table 1

For each aircraft size, we will simulate boarding using four methods of ordering: front to back, back to front, random order, and window_seats_first (i.e; window, middle, then aisle seat). By systematically varying these parameters and analyzing the results, we can identify the optimal boarding strategy for each aircraft size and provide evidence-based recommendations.

Methodology

Setup and simulation initialization

In each round, we initialized and ran a simulation for each of the 12 possible configurations (3 aircraft sizes and 4 ordering methods). For every simulation, we set the random seed equal to the round number so that the service times generated in each simulation within a round are the same. The function *run_simulation* was used to simulate a boarding process which returns the variables *total_time* (time to board all passengers)*, avg_time_in_aisle* (average time a passenger spends standing in the aisle)*, and avg_P_in_aisle* (average number of passengers standing in the aisle at any time).

During a simulation, passengers enter the plane and walk down the aisle until they either reach the row of their seats, or they cannot move any further due to congestion in the aisle. Once a passenger has reached the correct row, they begin loading their baggage in the overhead bin before accessing their seat. The time required to store baggage is generated according to an exponential distribution with a mean of 3. The time required to access the seat is generated according to an exponential distribution with a mean equal to 2x(number of passengers blocking + 1). The number of passengers blocking is the number of seated passengers in that row that are between the aisle and the desired seat (e.g; if a passenger is accessing a window seat but there are already passengers sitting in the aisle and middle seats, then the mean access time will be 2x(2+1)=6).

In our code, we use four different orderings to fill the plane. The function used to create these is called and stored as:

```
all_orders = create_orderings(plane_rows, plane_cols)
```

1. “back_to_front” ordering is created by splitting the passengers into 3 zones for the front, middle, and back of the plane. Then, the order of the passengers within each zone is randomized and the final order is created by concatenating these randomized groups in the order [back, middle, front].
2. “front_to_back” ordering is similar to *back_to_front* ordering except that the final ordering is created by concatenating the randomized groups in the order [front, middle, back].

3. "random_order" is created by generating a list of passengers and shuffling it randomly.
4. "window_seats_first" ordering is created by appending passengers with window seats, shuffling them, and the next column of seats (if there are more than 2 columns), followed by the aisle seats also in a random order.

Each ordering method still includes randomness along one dimension, as it is unrealistic to expect passengers to be ordered perfectly in a real-world scenario. After running a simulation for an ordering and aircraft size, it appends the results to three different dictionaries: *total_time*, *avgs_time_in_aisle*, and *avgs_P_in_aisle*. Finally, it increments the *total_sims* counter by 1 for each simulation. To generate our results, we ran 1000 rounds of simulations, 12,000 simulations in total.

The objective of this study is to investigate the most efficient method for boarding passengers onto an airplane, with the goal of reducing overall boarding time. Our hypothesis is that the "window-in" method will result in the shortest total loading time on average. Additionally, we anticipate that having more passengers in the aisle would lead to faster loading times, and thus we expect to observe more passengers in the aisle with the window-in method. By analyzing the boarding times for both methods, we hope to gain insights into the factors that contribute to efficient boarding, which can inform future boarding procedures and improve the passenger experience.

Data Collection

To measure the effectiveness of the different onboarding methods, we will collect data on the total time it takes to load the plane, which will be measured as the time when the last passenger is seated. Additionally, we will track the average time that each passenger spends waiting to sit down at their seat, as well as the average number of passengers standing in the aisle at any given time during the boarding process.

How we measure the total time it takes to load a plane

The **total_times** dictionary stores the total time it takes to fully load a plane for each combination of plane size and boarding method. During each simulation run, **total_time** is computed in the **run_simulation** function and then appended to the appropriate list in

total_times. The values in each list are later used to compute the average total time across all simulations for each combination of plane size and boarding method.

Then, the average total time for each combination of plane size and boarding method is computed by summing up the values in the appropriate list in **total_times** and dividing by the total number of simulations (**num_sims**). The round function is used to round the result to one decimal place.

How we measure the average time each passenger takes to sit down

It is important to note, we start this time measurement from the time the passenger is in the plane. The time measurement for passenger service starts from the moment they enter the plane. "**service_end_time**" indicates when the passenger takes their seat, while "**arrival_time**" denotes when they boarded the plane. To keep track of these values for each customer "i," we maintain a list in our simulation. By summing up these times and dividing by the total number of passengers, we determine the average time standing in the aisle for that simulation.

avg_time_in_aisle = sum([service_end_time[i] - arrival_time[i] for i in range(num_passengers)]) / num_passengers

How we measure the average number of passengers standing in the plane aisle

After the while loop in the run_simulation function, the plane reaches full capacity in terms of passengers occupying the aisle. At this point, we count the number of passengers who are left standing:

number_of_p_in_asile = len([x for x in aisle_rows if x != -1])

We advance the clock to the time when the next passenger takes their seat, which allows us to record the elapsed time during which some passengers were standing.

time_elapsed = next_event[0] - clock

These values are stored as:

p_in_aisle_for_this_long.append((**number_of_p_in_asile**, **time_elapsed**))

Once this round of simulation is completed, a function called **getAvg_p_in_aisle** finds the average number of passengers standing in the aisle at any one time.

Statistic Evaluation

To evaluate the effectiveness of each configuration of the simulation, we will calculate the average for each run. By examining the results of each configuration for each plane model, we can determine the optimal configuration for a specific aircraft. We will then evaluate the averages for each configuration across all plane models to identify the overall best configuration. This will help us draw more robust and reliable conclusions about the effectiveness of each configuration, and make data-driven recommendations for improving the aircraft onboarding process.

Results and Analysis

Individual Runs

AVERAGE TOTAL TIME

Plane Size	Back to Front	Front to Back	Random	Window
small	92.1	111.3	88.6	76.0
medium	146.0	177.8	132.7	112.6
large	372.7	434.6	309.4	219.9

AVERAGE TIME IN AISLE

Plane Size	Back to Front	Front to Back	Random	Window
small	11.3	11.1	8.4	7.1
medium	16.8	16.7	10.7	8.8
large	28.2	28.5	16.0	10.6

AVERAGE P IN AISLE

Plane Size	Back to Front	Front to Back	Random	Window
small	3.0	2.4	2.3	2.3
medium	5.8	4.7	4.0	3.9
large	9.8	8.5	6.7	6.3

Our hypothesis was that the "window_seats_first" method would result in the shortest total loading time on average. Additionally, we anticipated that having more passengers in the aisle would lead to faster loading times, and thus expected to see more passengers in the aisle with the window-in method. However, our findings were unexpected: the "back-to-front" method had the highest average number of passengers in the aisle at any given time despite being the slowest method of boarding.

Grand Statistic Evaluation

Based on the output, our expectation that the window_seats_first ordering would produce the fastest average total time to load was correct. For all plane sizes, the window_seats_first ordering had the shortest average total time compared to the other three orderings. However, our prediction that more passengers in the aisle would result in more passengers being able to get to their seats was not confirmed. In fact, the ordering with the highest average passengers in the aisle was not associated with the lowest average total time. It seems that the correlation between average passengers in the aisle and average total time is not as straightforward as we initially thought.

The simulation results confirmed our hypothesis that the window_seats_first ordering is the fastest method of loading for all plane sizes. This is likely due to the fact that this ordering completely avoids the scenarios where a passenger with a window seat has to step over a passenger who has already sat down in the aisle seat of the same row.

As for the average passengers in the aisle, the results show that the window_seats_first ordering did not produce the highest number of passengers in the aisle, contrary to our expectation. Instead, the back-to-front ordering resulted in the highest number of passengers in the aisle for small and medium planes, while the front-to-back ordering resulted in the highest number of passengers in the aisle for large planes. This could be because the back-to-front and front-to-back orderings require passengers in the same row to take their seats at the same time, resulting in more passengers being in the aisle at the same time.

Discussion

Insights and improvements for next time

Our simulation provides a foundation for further research into the boarding process of aircraft with 2 aisles. Future studies could build upon the current model to investigate how passenger behavior and airline policies impact boarding times in these types of aircrafts. By basing the baggage-storing times on statistical data and experimenting with variable rates of passengers with baggage, the simulation can better represent real-world boarding scenarios. Overall, the simulation model presented in this study has the potential to inform policy decisions aimed at improving boarding times and passenger experience on commercial airlines.

Reflection

The window-in ordering performed the best for our first goal with an average total time of 219.9 which was significantly faster than the other methods. The window-in method also performed best for our second goal of customer comfort, however since passengers traveling together book adjacent seats in the same row this method will force them to enter the plane separately. Because of this we believe that the random ordering method performed the best for our second goal.

Conclusion

In conclusion, this report presents a simulation project that aims to optimize the process of boarding passengers onto an aircraft. The simulation model analyzed two key metrics: the total duration of the boarding process and passenger comfort, measured by the time passengers spend standing on the plane and the average number of passengers standing in the aisle. The project varied two key parameters: the size of the plane and the ordering of passengers as they entered the plane. The results of the simulation showed that the window_seats_first ordering produced the fastest average total time to load for planes of all sizes, with the completely random ordering being second fastest. Additionally, the window_seats_first ordering did not produce the highest number of passengers in the aisle, contrary to initial expectations. These findings provide insights into how to optimize the boarding process for different aircraft sizes and could lead to improved customer satisfaction and potential cost savings for commercial airlines.