CSC446 GROUP PROJECT

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“An aircraft onboarding process simulator”

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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 minimize this metric so that each airplane may complete more flights, thereby increasing revenue. The second metric of passenger comfort is more complex and is measured by both the time passengers spend standing on the plane as well as the average number of passengers standing on the plane at any one time. Passengers may find it uncomfortable to spend long times standing on the airplane when they could be sitting inside the airport waiting to enter the plane. Similarly passengers may find it uncomfortable to stand in an airplane when the aisle is completely full. Through experimental analysis of our simulations we will determine the best methods of ordering passengers in order to optimize the boarding process for these metrics.

Parameters

To simulate the boarding process, we will vary two key parameters: the size of the plane and the ordering of passengers as they enter the plane. The 3 plane sizes that we will analyze are based on typical commercial aircraft used for domestic and international flights in Canada. The sizes will vary the number of seat rows as well as the number of seat columns on either side of the aisle and will correspond to small, medium, and large planes.

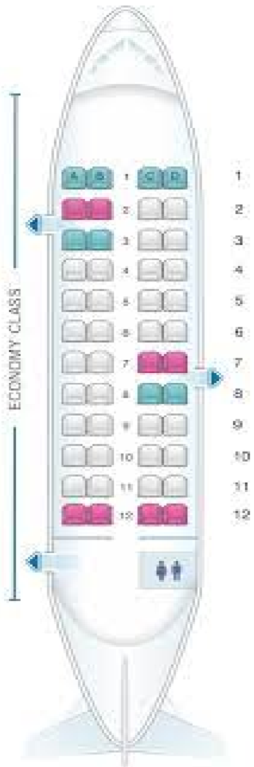
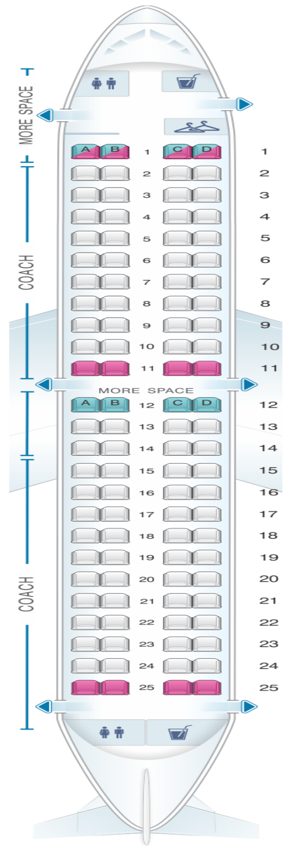
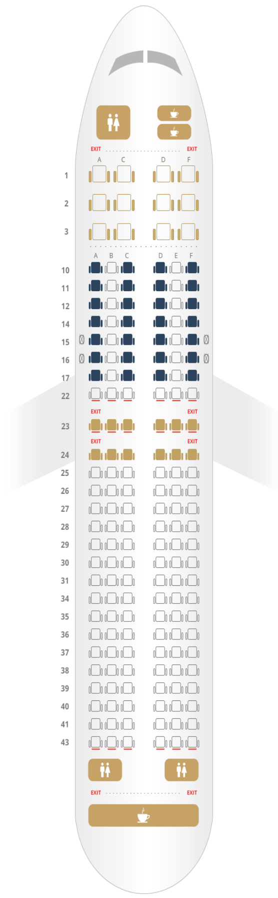
Size	Small	Medium	Large
Aircraft	Antonov An-24	Embraer e-jet Family	Boeing 737
Rows	12	25	43
Seats Per Row	4 (2, 2)	4 (2, 2)	6 (3, 3)
Images	 Figure 1	 Figure 2	 Figure 3

Table 1

Then for each plane size we will simulate boarding using 4 different methods of ordering including boarding front to back, back to front, random order, and outside-in (eg. for large plane load window seats first, then middle, then aisle seats). By systematically varying these parameters and analyzing the results, we can identify the optimal boarding strategy for each plane size and provide evidence-based recommendations to airlines and airport authorities.

Methodology

Setup and simulation initialization

In this simulation study, we aimed to measure the effect of different ordering methods on the boarding process of commercial airliners. In each round we initialized and ran a simulation for each of the 12 possible configurations (3 plane 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 either they 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 and then access 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 eg. if a passenger is accessing a window seat but there are already passengers sitting in the aisle & 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 ie. it would be impractical from an airport to call each row of seats up for boarding one-by-one.

After running a simulation for an ordering and plane size, it appends the results (total time, average time in aisle, and average passengers in aisle) to three different dictionaries based on the plane size and ordering. Finally, it increments the total number of simulations counter by 1 for each simulation. To generate our results we ran 1000 rounds of simulations which involved 12,000 simulations in total.

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 in the plane, as well as the average number of passengers standing in the plane aisle at any given time during the boarding process. This data will allow us to compare and contrast the various onboarding methods and determine which method is the most efficient in terms of reducing the overall time it takes to board the plane while also minimizing the amount of time passengers spend waiting in line or standing in the aisle. By collecting this data, we hope to gain insights that will enable us to improve the onboarding process and enhance the overall travel experience for passengers.

How we collect total time it takes to load the 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 collect 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 collect 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. The use of statistical analysis in this simulation project will help us to draw more robust and reliable conclusions about the effectiveness of each configuration, and make data-driven recommendations for improving the onboarding loading process of airplanes.

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-in" 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, it appears that our expectation that the window-in ordering would produce the fastest average total time to load was correct. For all plane sizes, the window-in 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 consistently 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-in ordering is the fastest method of loading for all plane sizes. This is likely due to the fact that the window-in 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-in 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

The simulation study presented here 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 planes. Additionally, by basing the carry-on baggage mean off statistical data, 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.

Conclusion

In conclusion, this report presents a simulation project that aims to optimize the process of boarding passengers onto an airplane. 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-in 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-in 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.