Modelling of aeroplane boarding & disembarking using cellular automata

2022 IM^{2}C - High Distinction

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Background

Airlines' revenue is dependent on their ability to keep aircrafts airborne for as much of the time as possible - that is, having as few delays as they can. Among the services an aircraft undergoes on the ground, the deplaning and enplaning of passengers accounts for much of the time that is used to prepare for the next flight[1]. As such, the optimisation of such a process is beneficial for both airlines and airports, enhancing punctuality and increasing the number of flights each gate or stand may service per day. Moreover, effective turn-around management reduces the individual boarding/disembarking time for passengers, allowing for greater customer satisfaction.

We started this investigation with the aim of establishing a model that determines the amount of time taken for a number of passengers (P) to embark and disembark under varying circumstances. We were able to model the travel time for a single passenger using the following equation:

$$T_{min} = \frac{T_r}{V} + \frac{T_s}{V} + T_{open} + n(T_{bag1}) + \frac{E}{V}$$

(T_{min} is the minimum amount of time it would take someone to seat - assume there are no bagging delays; T_r is the target row;
T_s is the target seat (1 corresponds with the interior seats, C and d;
2 with middle seats B and E; 3 with window seats A and F);
V is the speed of the person;
T_{open} is the time it takes to open the overhead bagging;
n is the amount of bags;
T_{bag1} is the amount of time it takes to stow 1 overhead bag;
E is the distance between the start of the queue and the first seat in the plane)

This describes the amount of time it is taken by 1 person to reach their spot in the plane, assuming there is no one blocking them. However, given that it was difficult to determine the number of blockages that would occur as a result of bagging, as well as taking into account seat shuffle, we decided to discard this approach and instead opt in for a more flexible one. In order to model the problem, we decided to develop and use an algorithm in order to calculate the range of times needed for boarding and disembarking under differing conditions. An adaptable cellular automaton (CA) is used here to simulate various scenarios, by using a collection of cells on a grid to represent the activities of the passengers. Written in python code, this allows for variability and testing of the program under different situations, as well as collecting data from these models.

Modelling the Plane Boarding Procedure

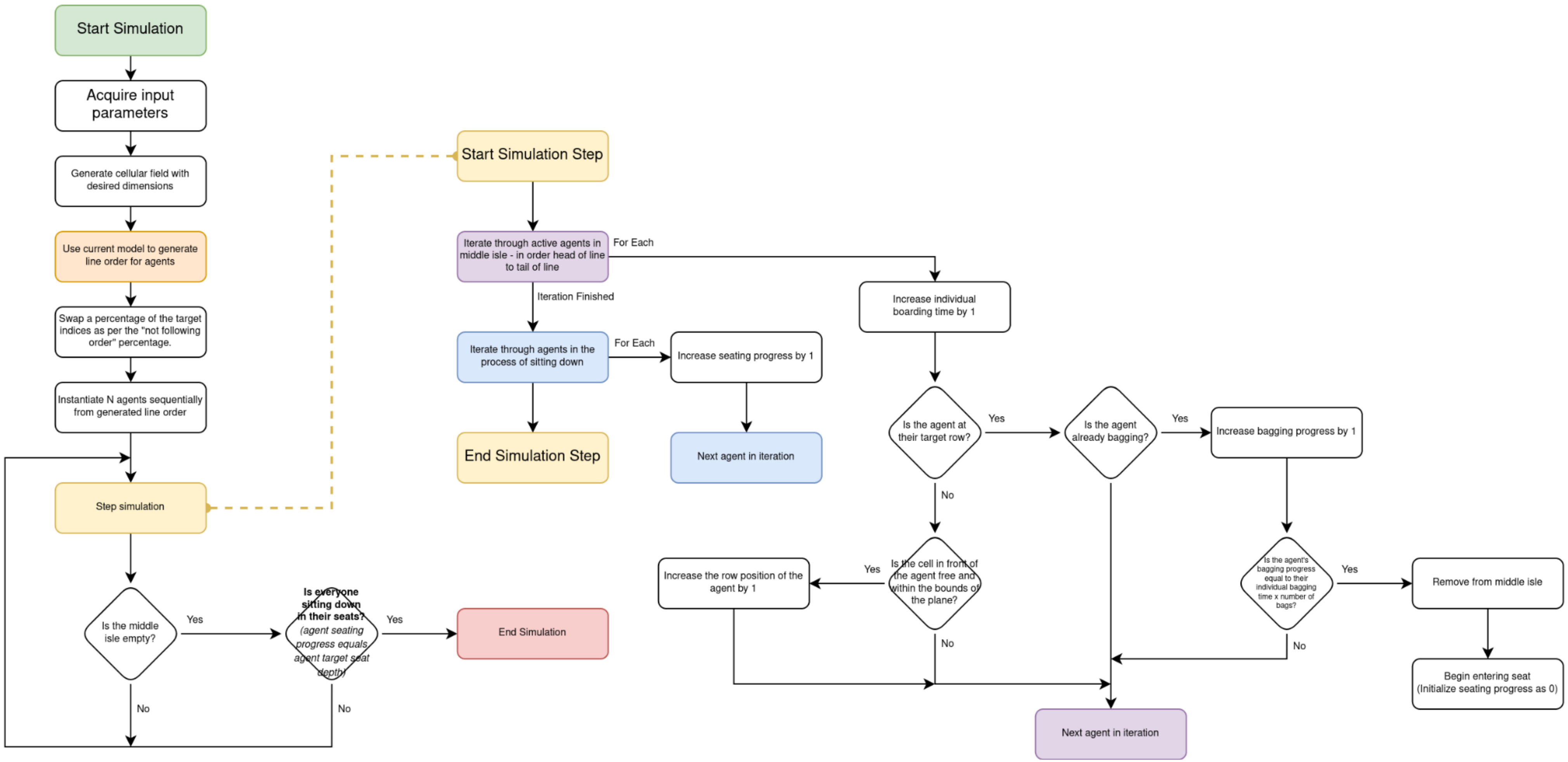
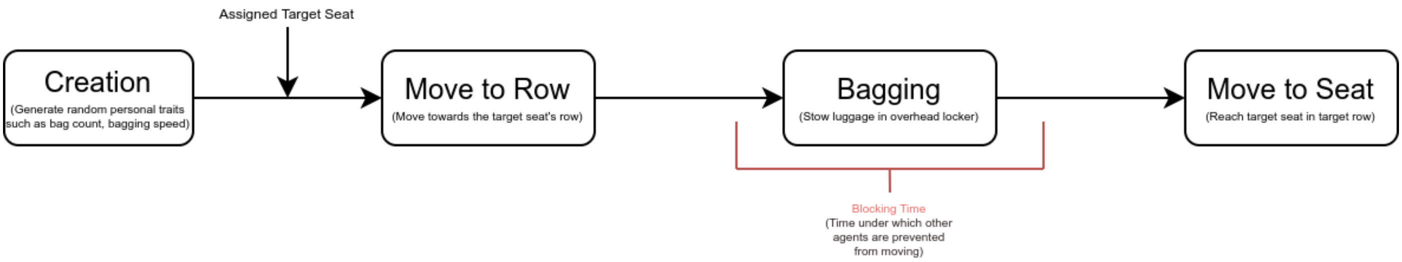


Figure 1: Flowchart of boarding simulation algorithm. Yellow block titled "start simulation step" signifies the process that the cellular automaton undergoes each iteration of its elife in order to produce the next generation of agents.

The plane embarking simulation was written and executed in Python repetitively, but its basic steps can be outlined in the flowchart, as seen in Figure 1. The libraries MatPlotLib, NumPy. This simulation allows for the changing of parameters if necessary, and its simple structure allows for the addition of complexity if necessary. For example accounting for people not following the orders is simply done by swapping some of the target indices in order to simulate people being in improper order. It also allows flexibility in changes to the simulation such as passenger saturation of the plane - using the cellular automaton, this is very simple to implement by simply instantiating less agents.

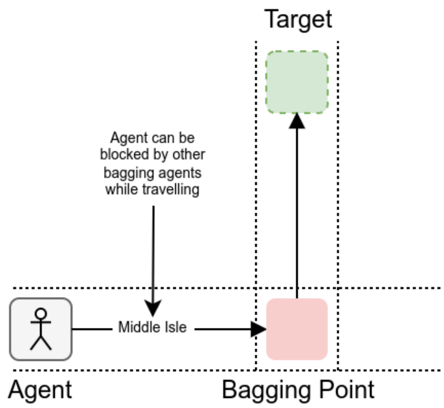
By assigning random values (within given constraints) to the agents' properties such as bagging time & bag count, the embarking time for all passengers would be different almost every time much like a real scenario. From this difference, a distribution can be made, which can assess the realistic maximum and minimum times for to embark on the plane.

The lifecycle of the agent effectively consists of four steps that are simulated:



1. **Creation** - This is the point at which the agent generates random "traits" for itself:
   a. Bag Count (random within boundaries)
   b. Time it takes to stow away one bag (random within boundaries)

   Between this step and the second, the simulator assigns the agent a target seat from the initial sorting order. As agents are created sequentially, this effectively simulates passengers queuing up and getting assigned a boarding group from the boarding method.
2. **Movement to Row** - The agent enters a loop in which they constantly attempt to advance forward one cell. This may or may not be possible, depending on whether there is another agent occupying the neighbouring cell in the way of the agent's path. An example where the agent cannot move is when another agent is bagging adjacent to them in the travelling direction.
3. **Bagging** - Once the target row is reached, the agent starts bagging luggage for a predetermined amount of time assigned during creation. During this time, the agent will refuse to move until it is finished bagging. During bagging, this agent is considered as "blocking" the other agents from advancing, as any agents preceding will refuse to move as well due to lack of a vacant spot.
4. **Movement to Seat** - Once bagging is complete, the agent immediately frees the middle aisle, and begins travelling to their seat. This travel time increases with the seat's distance from the centre, and depending on already present occupants of seats in the same row obstructing a path between the agent's target seat and the middle aisle.



After running the simulation 1000 times (with 198 passengers per flight, a variation of 5 to 20[1] seconds in time taken to bag, and variable bag counts), the distribution of the average per-passenger boarding time can be conclusively modelled from the gathered sample.

Manner in which boarding is sorted	Boarding Time (s)		
	Low (5th Percentile)	High (95th Percentile)	Mean
Unstructured	746.42	946.42	842.51
Grouped aft to front, unstructured within group	1071.26	1307.81	1185.39
Grouped by seat, closest to middle aisle last	329.46	446.19	384.62

Table 1 - Comparison of boarding times based on boarding sort order, assuming 5% disobedience and 1-3 bags of carry-on luggage to stow away

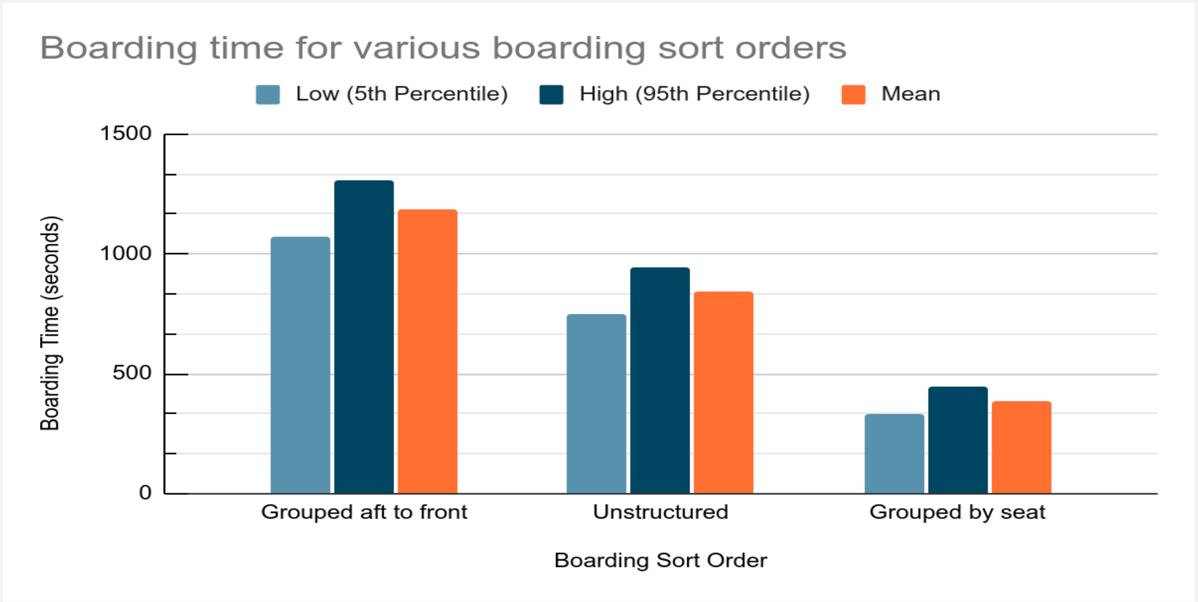


Figure 2 - Visualisation of boarding times based on boarding sort order, assuming 5% disobedience and 1-3 bags of carry-on luggage to stow away

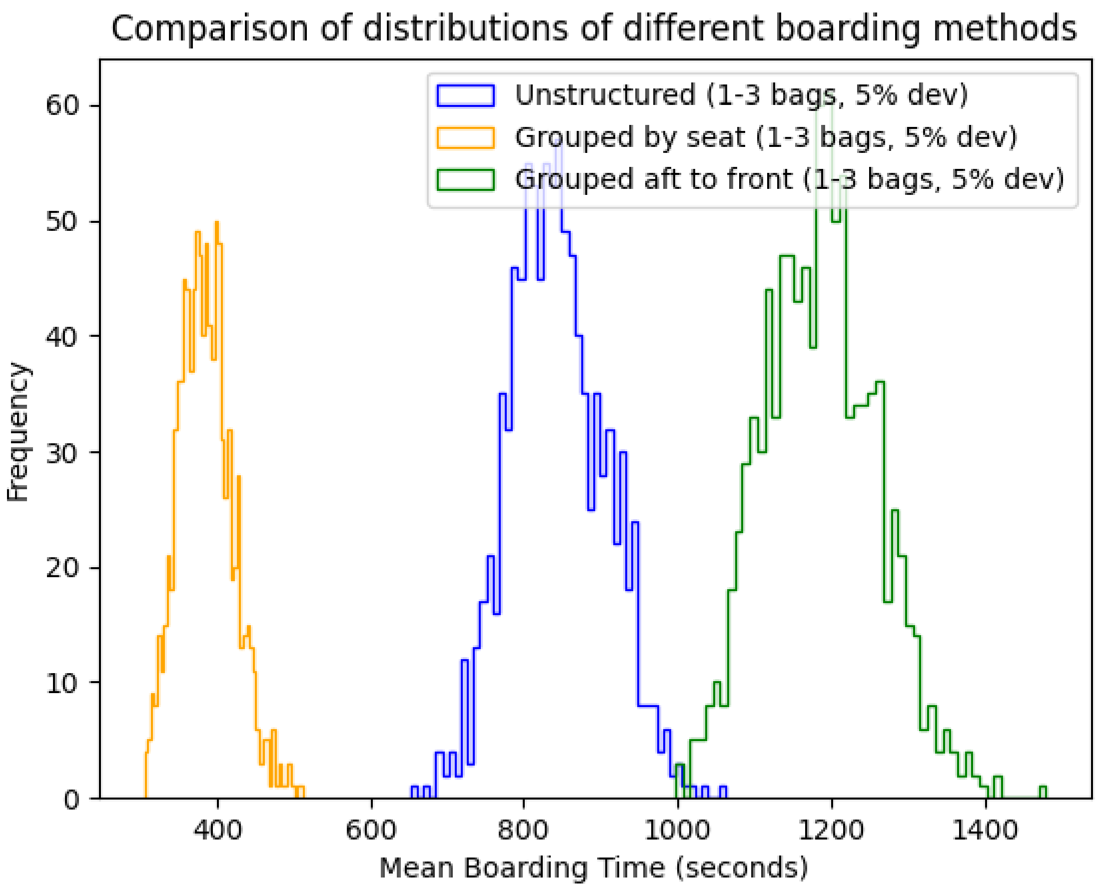


Figure 3 - Distributions of personal boarding times for different boarding methods, assuming 5% disobedience and 1-3 bags of carry-on luggage to stow away

Most airlines limit the number of carry-on bags to be 2, or one large carry-on. Therefore, it is reasonable to assume that most passengers would take 1-2 pieces of carry-on luggage[1]. By allowing for people to carry 3, we can account for exceptions to the airline's rules such as people bringing small objects with them, like laptops, and taking time to stow them. Assuming that 5% of passengers simply do not follow the boarding method and choose their own spot in the boarding queue, and that each person is carrying a realistic amount of carry-on luggage (1-3 bags)[1] - the alternate boarding methods make a distinctive difference upon the average boarding time.

It can be observed from Figure 2 that the seat grouping method features the lowest 5th and 95th percentiles, followed by an unstructured approach, and finally, ironically the most used airline boarding method[2] performs worse than the completely unstructured approach. Figure 3 illustrates this with more granularity by showing the distributions of average per-passenger boarding times across simulations, which illustrates that not only is the seat grouping method (pictured in yellow) the fastest, but also the most consistent, with most values lying towards the centre of the bell curve. This can be attributed to the fact that while the other two methods take little to no measure to minimise collisions in the middle aisle for bagging passengers, the outer to inner seat method ensures that these collisions are minimal. Assuming that the

[1] https://www.flightcentre.com.au/flights/planning-your-flight/baggage-guide
[2] https://doi.org/10.1371/journal.pone.0242131

range of bagging time for an airline passenger is around 5-20 seconds[3], it is adequate to surmise that the majority of passenger delays in boarding would come from slow-bagging passengers. Therefore minimising this time would provide the greatest benefit to performance, hence the overwhelming success of outer-to-inner seat boarding.

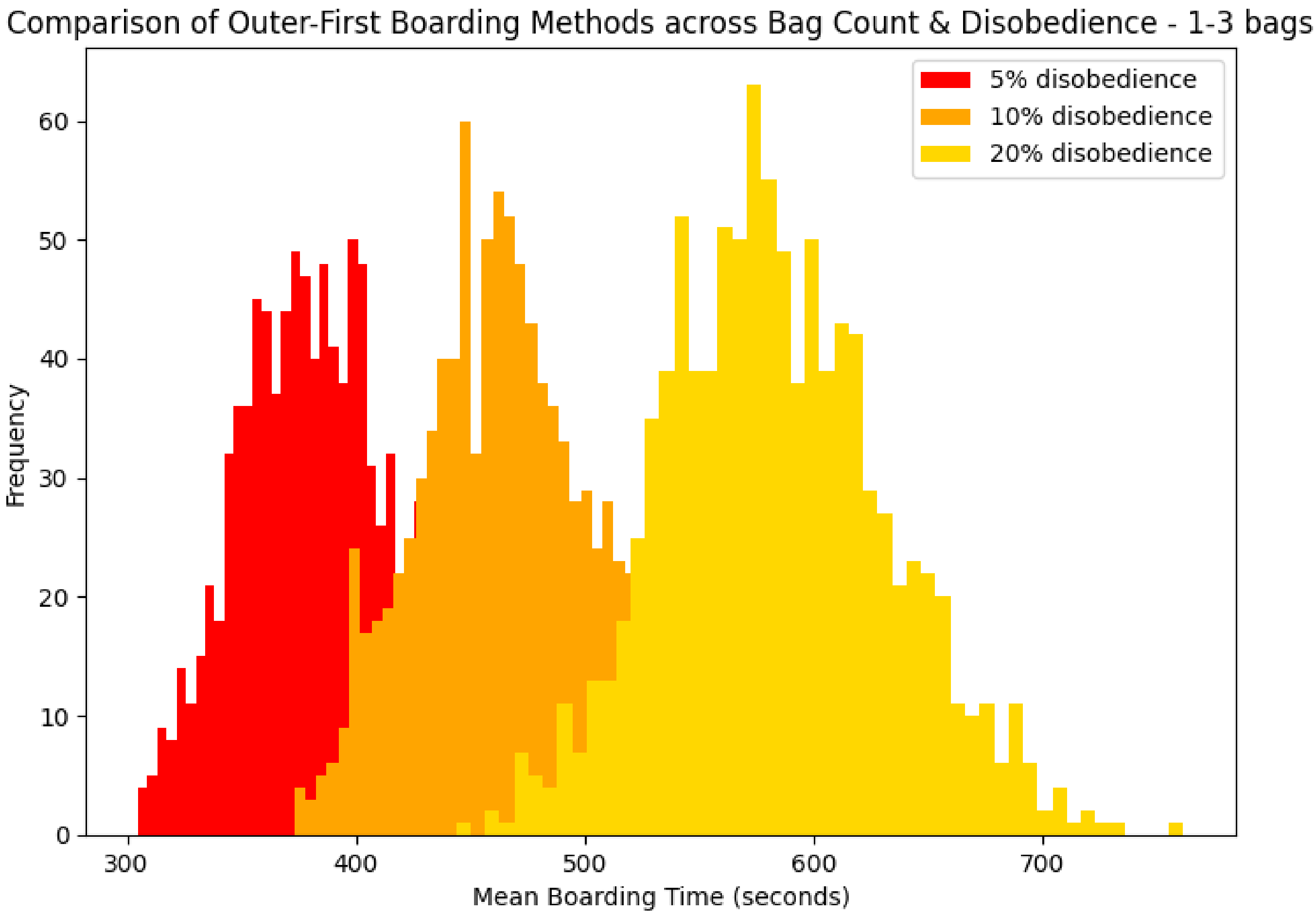


Figure 4a - The spread of mean boarding times for outer-first boarding altered by percentage of noncompliant passengers to boarding order (percentage disobedience), for a spread of 1-3 carry-on bags.

One of the limitations of efficient methods is how much the boarding time can differ when people do not follow the rules. In many cases, passengers will ignore the rules either because they misunderstand them, or it would be an inconvenience for them to follow. The percentage of pass

[3] Obtained from https://www.researchgate.net/profile/Michael-Schultz-20/publication/263038949_Efficiency_of_Aircraft_Boarding_Procedures/links/59861f0f0f7e9b6c8534925e/Efficiency-of-Aircraft-Boarding-Procedures.pdf

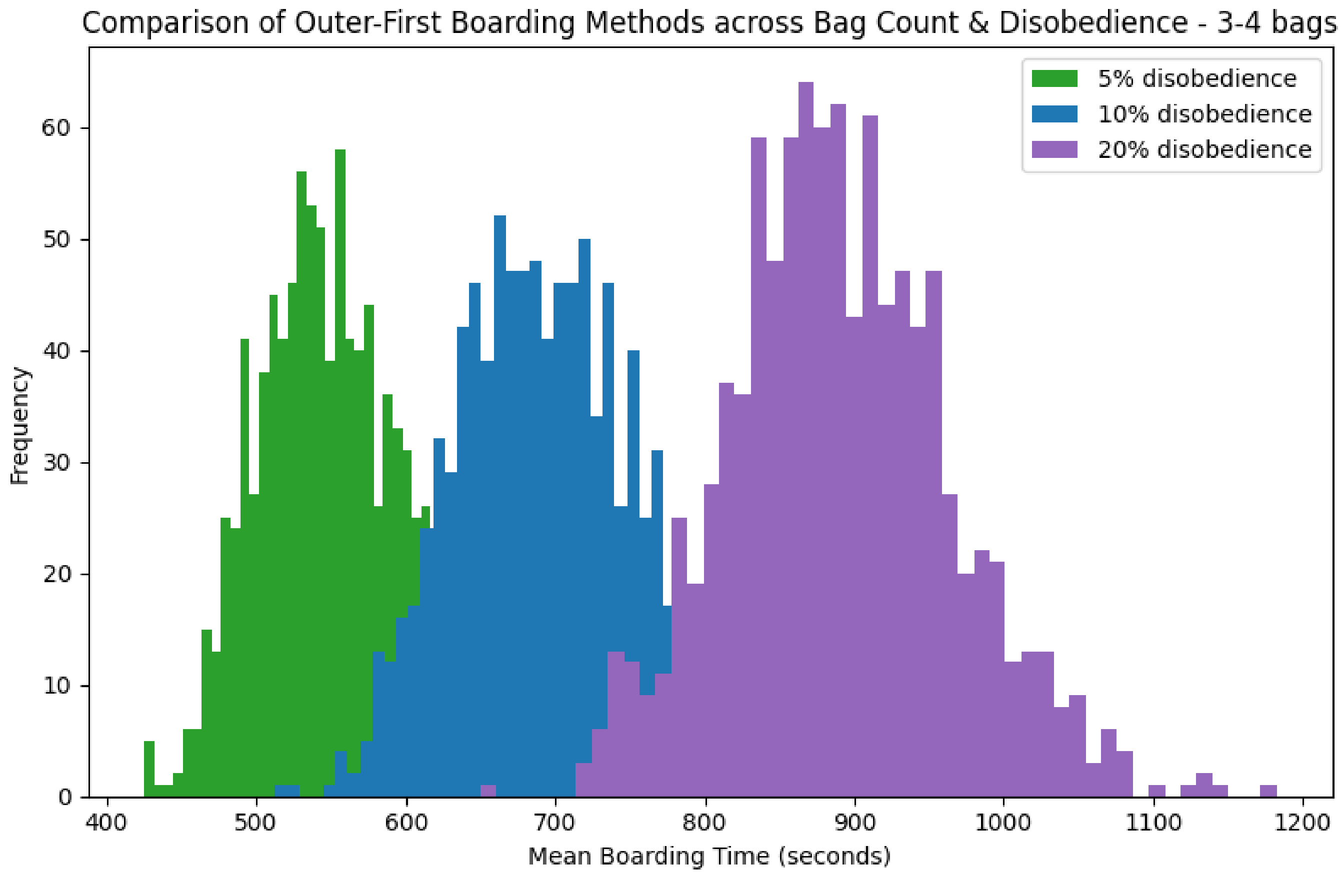


Figure 4b - The spread of mean boarding times for outer-first boarding altered by percentage of noncompliant passengers to boarding order (percentage disobedience), for a spread of 3-4 carry-on bags.

Percentage disobedience	Number of bags	Mean of boarding times (s)	Percentage change from base case
5% (Base case)	**1-3**	384.6	N/A
	3-4	*551.7*	*N/A*
10% (2x base case)	**1-3**	468.8	21.88%
	3-4	*699.4*	*26.77%*
20% (4x base case)	**1-3**	583.5	51.70% (+29.82%)
	3-4	*890.5*	*61.4% (+34.64%)*
100% (Unstructured boarding)	**1-3**	842.5	119.1% (+67.3%)
	3-4	*1334.2*	*141.8% (+80.4%)*

Table 2 - Tabulating the mean of boarding times according to percentage disobedience, calculating the percentage change from the base case for outer-first seat boarding.

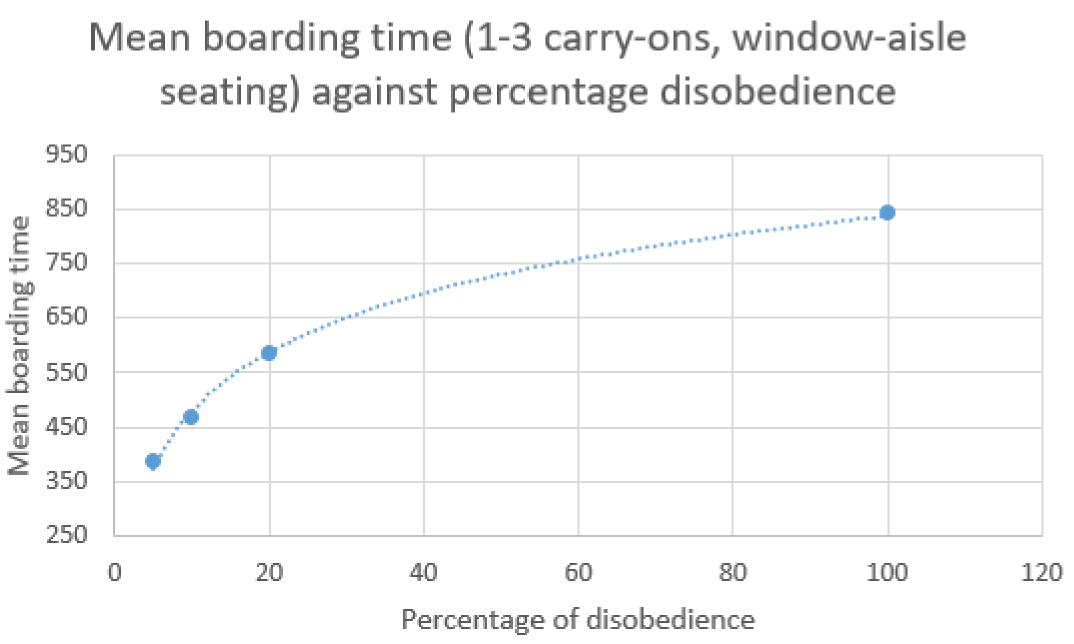


Figure 4c - Mean boarding time against the percentage of disobedience, created with data from Figure 4a. When 100% are disobedient, the boarding order is, in effect, completely unstructured.

As may be observed through Figures 4a and 4b, increasing noncompliance to boarding order by passengers causes a shift in the distribution of mean boarding times toward a distribution that closely resembles the distribution of mean boarding times when boarding order is unstructured. Interestingly, when there is a fourfold increase in the number of noncompliant passengers, there is only a rough doubling of the percentage change in mean boarding times (as per Table 2). When compared to completely unstructured boarding, it becomes clear that the rate at which the mean of boarding time increases is not constant - rather, it slows as it approaches the approximate random mean of 842.5 seconds. This has been visualised in Figure 4c, with the logarithmic trendline approximating the average mean of points that were not trialled. Given the shape of the trendline, which suggests a decreasing rate of change, it is shown that the sensitivity of the data to the percentage of noncompliant passengers decreases as the latter increases. The same behaviour may be expected from the average boarding times where carry-ons per passenger range from 3-4.

Analysis of Aft-First Grouped Boarding

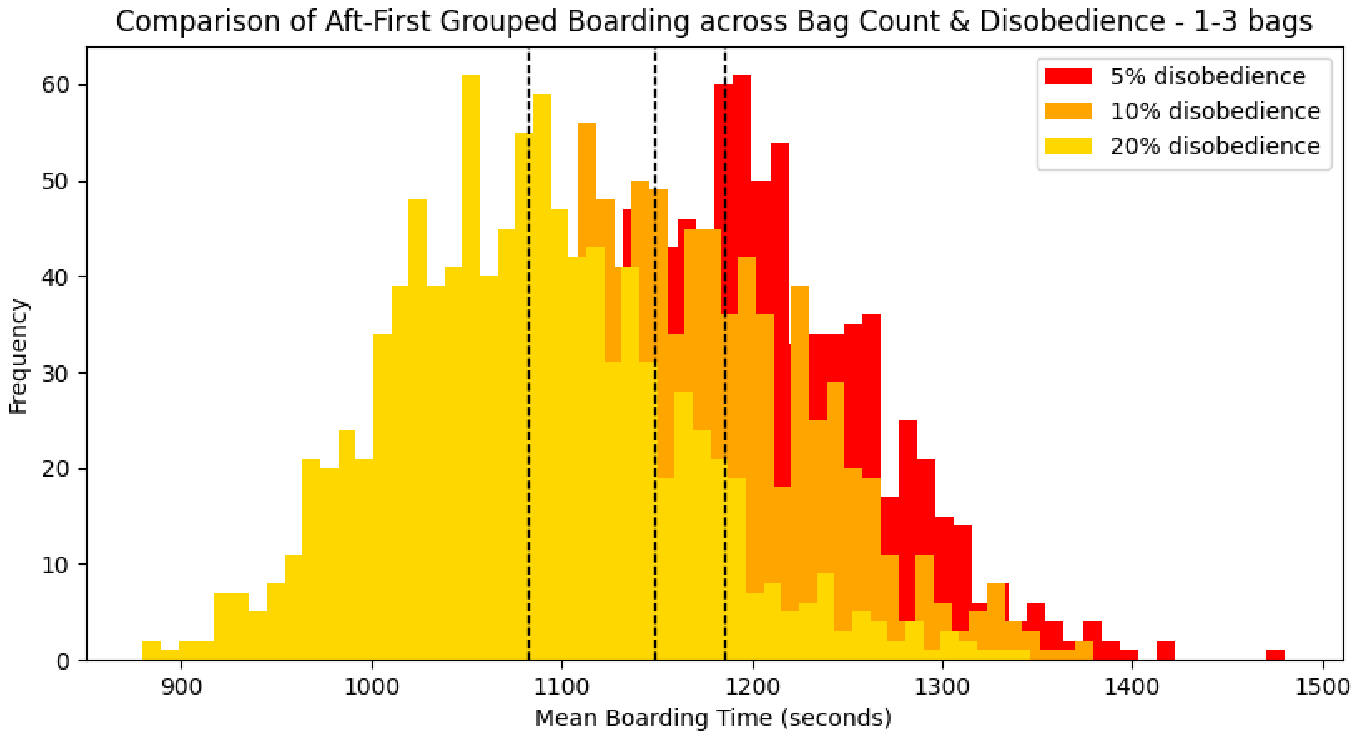


Figure 5a - The spread of mean boarding times for aft-first grouped boarding altered by percentage of noncompliant passengers to boarding order (percentage disobedience), for a spread of 1-3 carry-on bags.

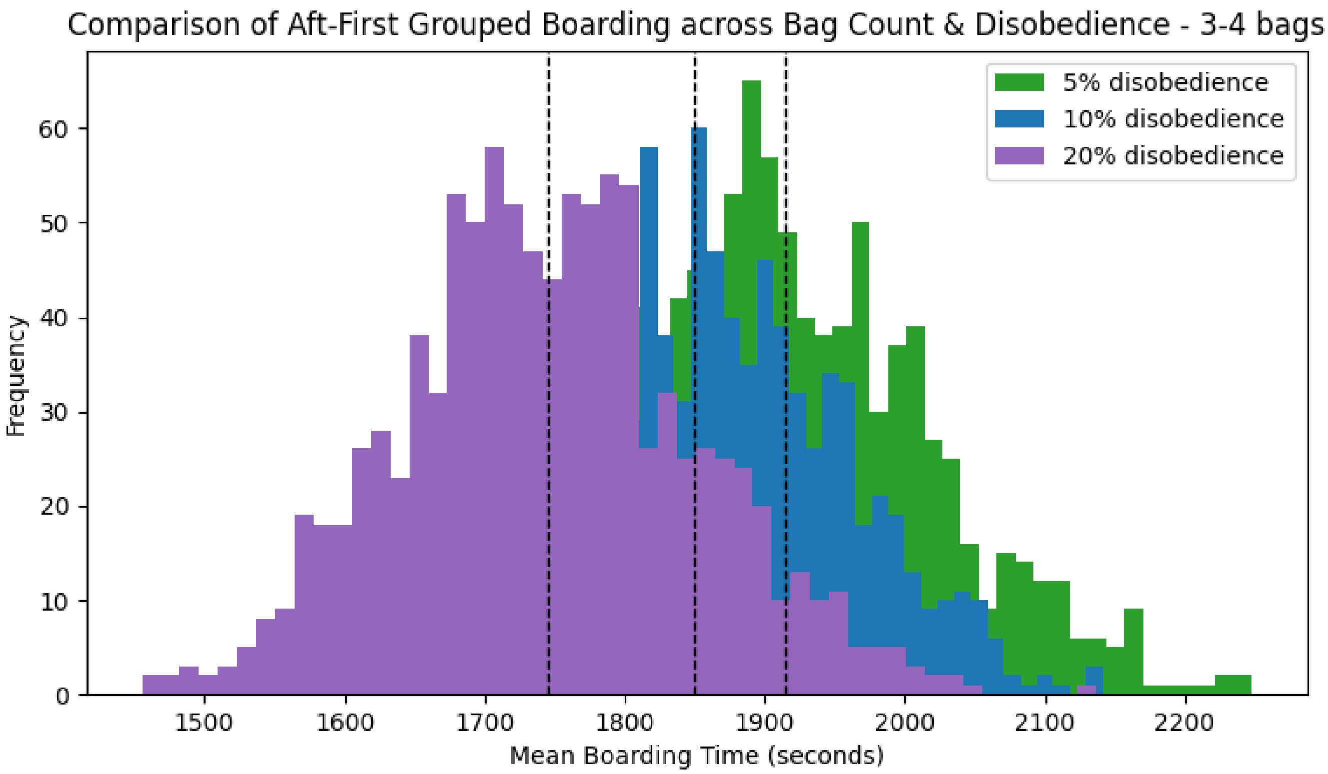


Figure 5b - The spread of mean boarding times for aft-first grouped boarding altered by percentage of noncompliant passengers to boarding order (percentage disobedience), for a spread of 3-4 carry-on bags.

Percentage disobedience	Number of bags	Mean of boarding times (s)	Percentage change from base case
5% (Base case)	**1-3**	1185.4	N/A
	3-4	*1914.4*	*N/A*
20% (4x base case)	**1-3**	1082.0	-8.72%
	3-4	*1745.6*	*-8.82%*
100% (Unstructured boarding)	**1-3**	842.5	-28.0% (-20.2%)
	3-4	*1334.2*	*-30.3% (-21.5%)*

Table 3 - Tabulating the mean of boarding times according to percentage disobedience, calculating the percentage change from the base case for aft-front group boarding.

As a nonoptimal boarding method, aft-first grouped boarding is positively affected by disobedience and randomisation. The effect of this is directly opposite to the effect as observed in the earlier section, rate of change included. Thus, it may be surmised that the sensitivity of the data to this increase in randomisation increases as randomisation increases.

Analysis of Random Boarding

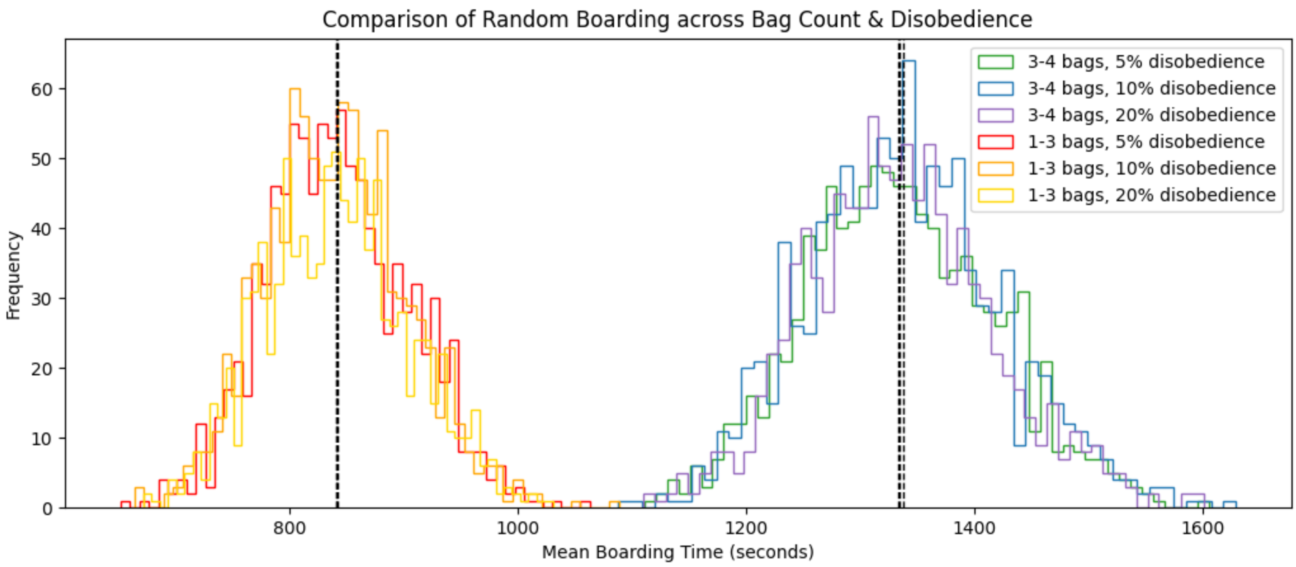


Figure 6 - Unstructured boarding is unaffected by disobedience (there are no rules to disobey). Note the large effect of increased baggaging: the warm colours depict situations where the average number of carry-ons is approximately 2, whereas the cool colours depict situations when the mean number of carry-ons is between 3-4.

According to Figure 3, the unstructured boarding strategy (complete randomization) is represented by the blue line. The green line shows the distribution of an nonoptimal boarding method (aft to front), and the yellow line represents an optimised situation (where passengers are grouped by seats columns, from window to aisle). It is shown that the unstructured boarding method takes more time than the “grouped by seat” strategy, while taking less time than the “aft-to-front” boarding method. As rates of disobedience increase randomisation, higher rates of disobedience in structured methods push mean results towards the mean results of unstructured boarding - thus, nonoptimal methods benefit from randomisation, whereas optimised methods do not. In Figures 4a & 4b, it appears that when the chance of randomization increases, the time for passengers grouped by seat to board becomes longer, whilst the time for another boarding method (grouped aft to front) decreases according to figures 5a & 5b.

Sensitivity to the number of carry-on bags

The situation where each passenger carries more bags than normal is visualised in the above figures. Examining the histograms of each boarding method, it can be seen that increasing the bag count consistently increases the distribution’s mean for the boarding method. Although there is *an* increase of the mean, different boarding methods’ distributions respond with a greater variance of the mean. For example, outer-first boarding is far more unaffected by the change in bag count when compared to random boarding (this may be observed in Figure 6, and by comparing Figures 4a and 4b). This can be explained by the fact that the outer-first boarding method aims to minimise the collisions between passengers on the middle aisle as a result of passengers occupying space while bagging their carry-ons.

Applying the CA to other aircraft seating configurations

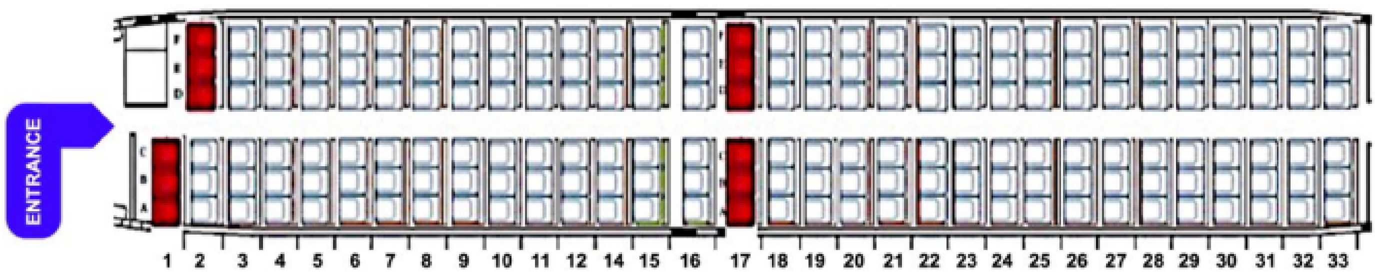


Figure A: “Narrow-Body” Passenger Aircraft

The CA has a very flexible structure with the ability to edit various parameters to create different situations with different aircrafts. As the “Narrow-Body” Passenger Aircraft (Pictured in Figure A was seen as the most relevant by the group, that was the aircraft type that the CA was adapted to. Due to time constraints, it was not adapted to any others, resulting in no data being able to be supplied about these scenarios. Furthermore, the rendering of these situations would be a lot more difficult, given their greater variability.

Best model

The factors that go into making the best model for a boarding method are: how responsive it is to disobedience, how intuitive the method is to follow, and how little congestion there is. Therefore, the most efficient method for boarding a plane must also be simple, since it must be practical. From CGP Grey’s “The Better Boarding Method Airlines Won't Use” video, we observed the “Family Model”, that was consistently outperformed by even random seating. However, it accounts for people who want to sit next to each other, as that is important in plane trips. Families often travel on aeroplanes and so do groups, hence it is the best model, as it is the most human. While it is outperformed by window-middle-aisle, and random, it outperforms grouped random, which is what is likely to occur in “random” scenarios.

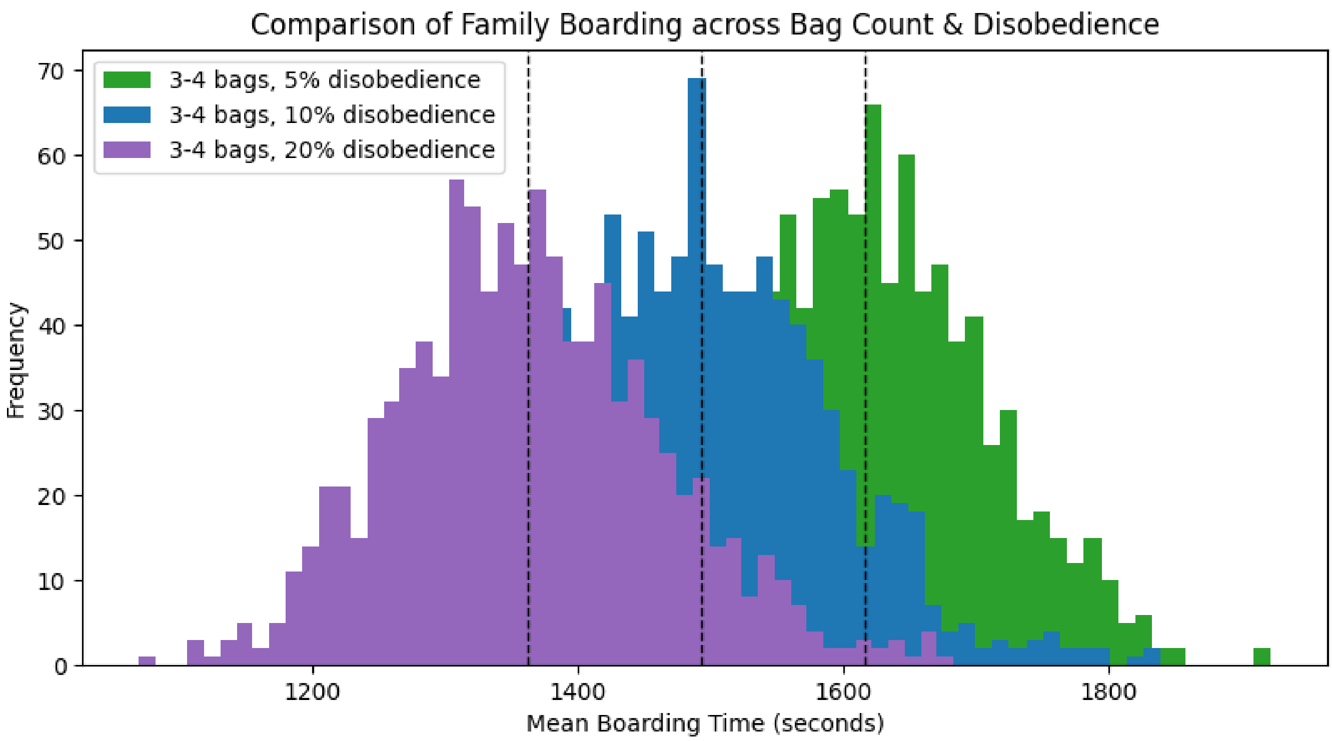


Figure 7 - The Family Model with individuals taking 3-4 bags, 5, 10, 20% disobedience

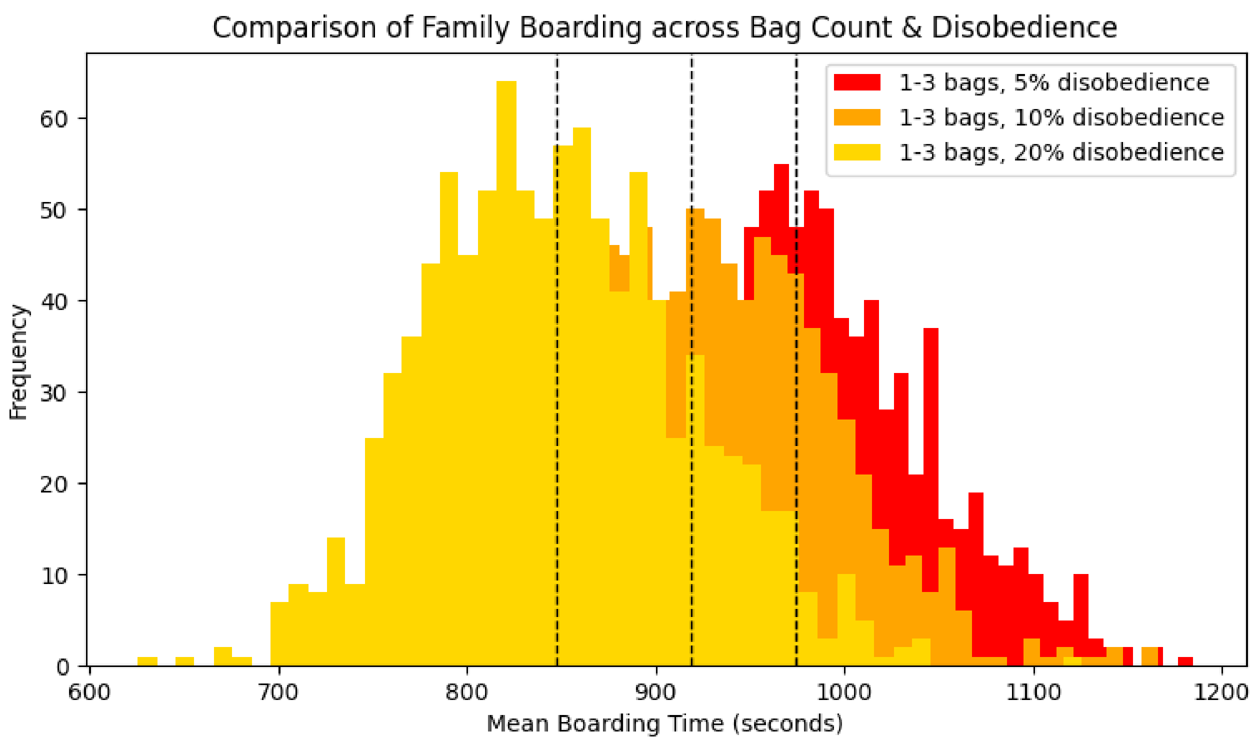


Figure 8 - The Family Model with individuals taking 3-4 bags, 5, 10, 20% disobedience

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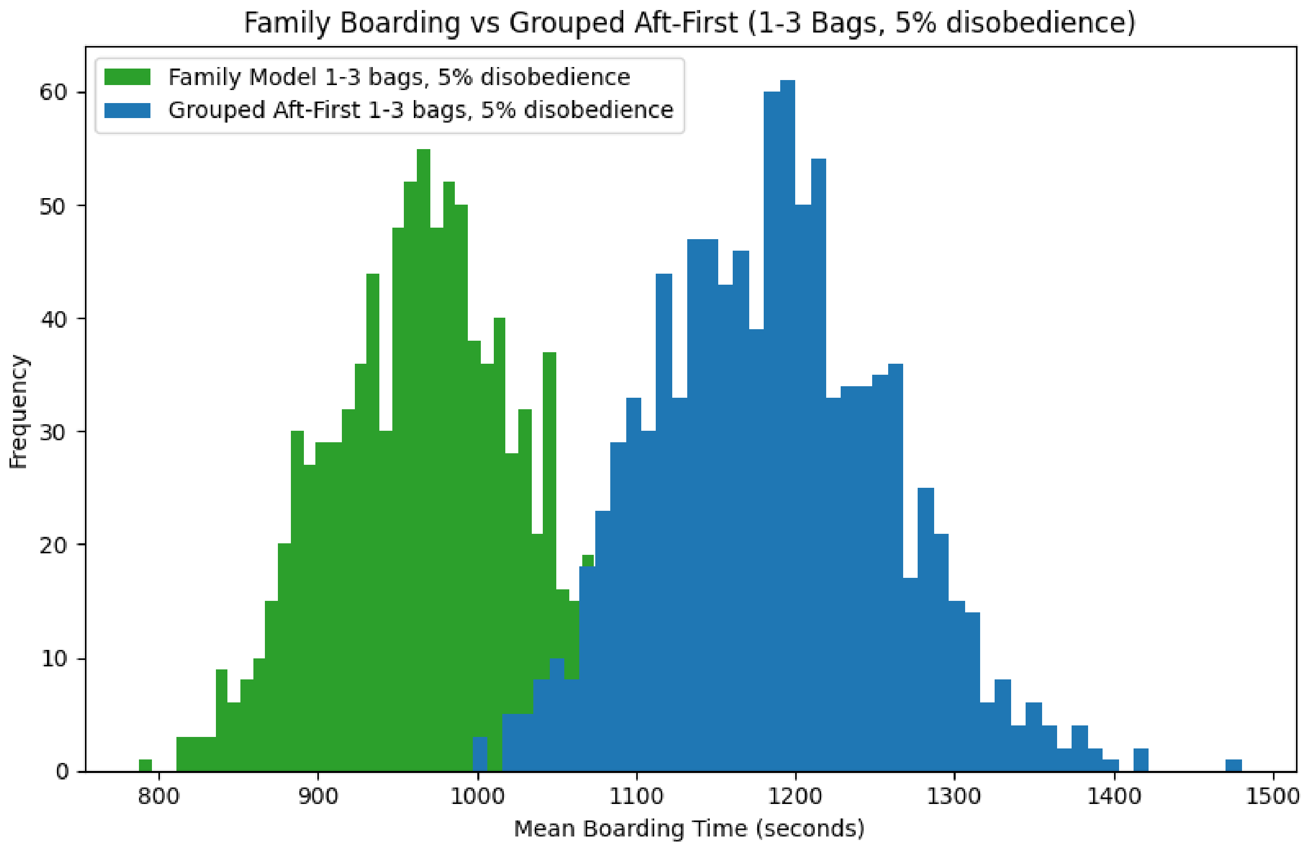
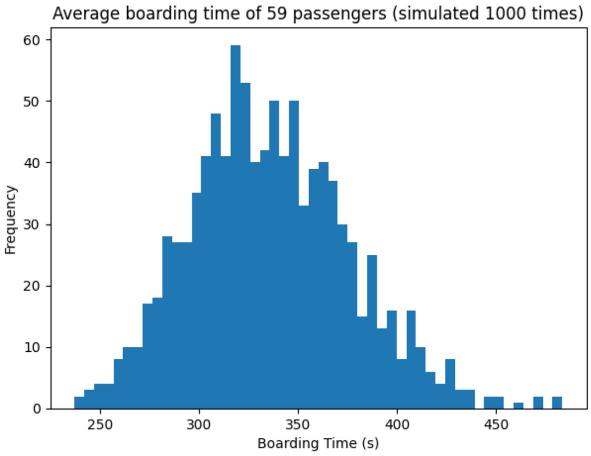


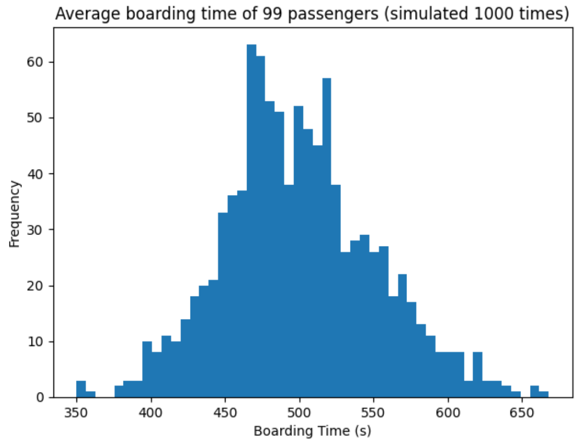
igure 9: The Family Model vs the Grouped Random Model

The Family Model lines people up so they can get into their row with ease. Every other aisle on the left side is assigned 1, and every opposite row (on the right side) is given value 2. Then, on the left side, every non taken spot is given value 3, and every non-taken spot on the right side is given value 4. This allows people to line up easily as they are given groups 1-4. From there, people are sorted such that the people at the back of the plane are at the front of the line, and the people at the front of the plane are put at the back of the line. The line is also sorted based on if they are by the window, in the middle or near the aisle. This allows families and groups of people to line up together, and is more efficient than grouped random boarding. Furthermore, though it's not seen within the simulations, families and groups take less time to bag, and in general have less bags than sums of individuals, as they have shared carry-on luggage. This would further increase the Steffen model's efficiency versus other methods.

As seen in *Figure 9*, the Family model is considerably more efficient than grouped random boarding, which is what true random boarding tends towards. So while being more human than any other model, it is also more efficient than its other human-friendly counterparts. Therefore, the Family Model is best for seating, as it is very human, takes into consideration groups and families, and is more efficient than other human methods. In terms of raw efficiency, window-middle-aisle is not beat, however.

Accounting for the Pandemic





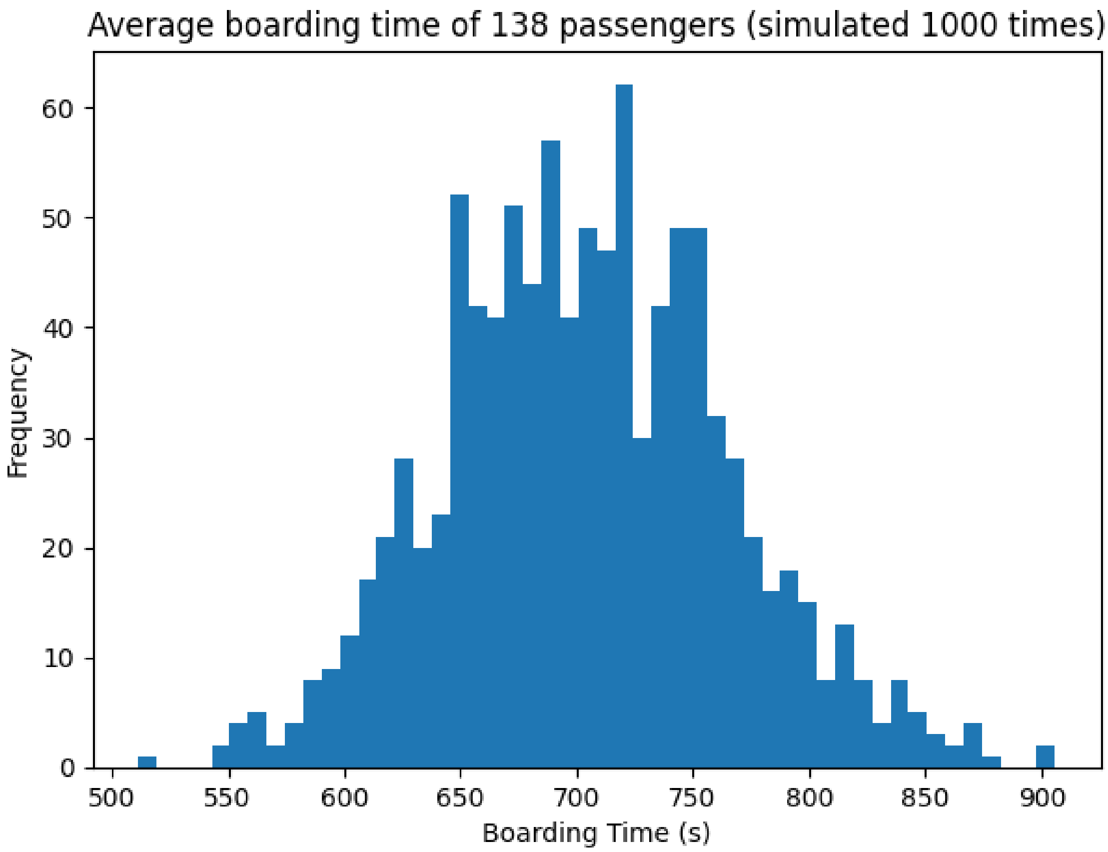


Figure 10 (top left) picturing family model at 30% plane capacity
Figure 11 (top right) picturing family model at 50% plane capacity
Figure 12 (bottom) picturing family model at 70% plane capacity

Plane Capacity (%)	Boarding Time (s)		
	Low (5th Percentile)	High (95th Percentile)	Mean
100	869.32	1090.63	974.52
70	607.08	810.48	704.47
50	419.82	589.76	499.9
30	274.37	406.9	336.29

Table 3 - Performance of family model at varying capacities

From figures 10, 11 and 12 it can be observed that the family model improves its performance based on a lower passenger count. This can be attributed to the lower number of collisions that can happen in the middle aisle, a factor that greatly hinders the original family model at 100% capacity. Despite this, it is important to note that enforcing the family model is extremely easy and may make it significantly easier for airline companies to control the spread of the pandemic and ensure a minimal number of infections can happen. The family model, by definition, also places family members (members of the same row) next to each other meaning that the chance of an infected passenger between healthy in the same row is low - a family would probably not travel if one of its members was infected.

Disembarking

Due to time constraints, we were unable to create a cellular automaton for the disembarking aspect of this, however it should be noted that due to the high flexibility of the algorithm, it should be trivial to go from boring to disembarking in terms of simulation. The same cannot be said for the model, unfortunately.

Different Plane Shapes

In a similar light, we were unable to create a cellular automaton for the different plane shapes. The flexibility of the model could be used in order to extrapolate the middle aisle to a 2D space, factoring in diagonals such as on the Single Wing Design, or multiple entry points for agents such as in the double entrance design.

Limitations

- Due to the nature of cellular automata, cells must be of a constant unit, and all agents must travel at the constant speed of 1 cell per cycle. In reality, this would be more granular, but here it is a limitation of the model.
- Due to the nature of cellular automata, the seats must have a constant distance between each other, meaning that a lot of space may be wasted whereas a real aeroplane would have a more efficient packing, therefore increasing the mean boarding times of our data.
- Due to time constraints, we have been unable to answer many required questions. We hope the existing information is useful.

Letter to the airline executive

25 March 2022

Dear Ed Bastian, CEO of Delta airlines,

I am writing to you to suggest a method for boarding and disembarking passengers that can apply to your airline, which we believe will minimise turnaround time and lead to more revenue. As we have tested the model from three perspectives: responsiveness to passenger disobedience, whether it is simple to follow, and aisle/seat congestion, we are confident that this will be of great contribution to your airline.

The strategy we investigated is based on an algorithm adaptable to different scenarios. We opted for this type of modelling because there is a varying range of potential variables under real-life conditions.Three conditions have been considered: aft to front, completely unstructured, and grouped by seat. The data indicate that the method" grouped by seat" has the lowest efficiency when applied to different scenarios, which is even worse than random boarding.

Through the previous analysis, the "Grouped by seat" method performed the best under all conditions even with a certain extent of disobedience. This suggests that the fastest boarding order will be passengers boarding window-middle-aisle. To achieve success in airport efficiency, airport workers should guide the passengers to line up in the order as we recommend before the flight.

The downside of enforcing the seat grouping model is that it would be hard to separate family members. For this, you suggest you use a "family model", which means people in the same row will line up in a queue together since it is one strategy that consistently outperforms others as a balanced compromise between speed and ease to follow.

You might also be interested in using the window-seat-method for business flights, where families may not be travelling together in order to minimise turnaround times.

Yours Sincerely,
HIgh DIstinction