Boarding—Step by Step: A Cellular Automaton Approach to Optimising Aircraft Boarding Time

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Summary

We model the boarding time for the aircraft using a cellular automaton. We investigate possible solutions and present recommendations about effective implementation.

The cellular automaton model is implemented in three stages:

- Initialisation of the seating layout for a chosen aircraft type and assignment of seats to passengers
- The sorting of passengers according to various proposed boarding methods
- "Propagating" the passengers through the aisle(s) of the aircraft and seating them at their assigned places.

The rules governing the automaton take into account various factors. Among these are the load factor (percentage filled) of the craft, different walking speeds of passengers walking through the aisle, and time delays from stowing luggage and obstructions by other passengers during the seating process. The algorithm accommodates predefined aircraft layouts of common aircraft and also user-defined aircraft layouts.

We modeled and tested various boarding strategies for efficiency with regard to total boarding time and average boarding time per passenger. Thus, our approach focuses not only on optimisation of the process in favour of

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the airlines, but also yields information regarding convenience to passengers. Random boarding (where passengers with assigned seat numbers enter the plane in a random sequence) was used as a point of reference. Among other strategies tested were boarding the plane in groups from either end, boarding from seats farthest from the aisles toward the aisles, and combinations of these approaches.

We conclude that boarding strategies starting farthest away from the entrance or farthest away from the aisles yield shorter boarding times than random boarding. The most successful methods are combinations of these strategies, their detailed implementation depending on the exact layout/size of the aircraft. The method yielding the shortest total boarding time is not necessarily the one with shortest average boarding time per passenger. By considering standard deviations of total and individual boarding times over many iterations of the simulation, we can derive conclusions regarding the stability/consistency of the specific boarding strategies and how evenly the waiting time is distributed amongst the passengers.

By selecting appropriate strategies, time savings of 2–3 min for small and medium aircraft could be achieved. For a custom 800-seat aircraft with two aisles, more than 6 min could be saved compared to random boarding. Having compared our results to actual turnaround times quoted by airlines, we believe them to be realistic.

Automata Theory and Its Relevance

A cellular automaton is an algorithm that determines the time development of a given system. If the algorithm is fed an initial configuration of the system, a finite set of fixed rules determines how the system develops. A time-step structure is used, such that the algorithm advances incrementally with all its rules being implemented at every time-step.

We used this approach to model various boarding strategies. We create a set of rules to govern how passengers move in the aisle(s) of a plane and what happens when they take their seats. Then we tested various strategies for boarding by changing the order in which passengers entered the plane. Ultimately, we made a comparison of relative boarding times for different strategies (averaged over many iterations), to select the most time-effective strategy. The algorithm was implemented in Matlab.

The Algorithm

The simulation consists of three main parts:

- an input vector of the passengers,
- a set of rules describing the behaviour of passengers in the plane, and

- a seating plan of the plane (flexible for various sizes/layouts of planes) represented as a matrix.

The arrangement of the input vector determines in which sequence passengers enter the plane. For instance, if the strategy is to board window-seat passengers first, the input vector would be sorted / arranged so that these passengers are at the "front" end of this vector. The vector (which is essentially a lookup-table) also contains the following information for each passenger:

- passenger number (to track elements moving through the matrices);
- seat number;
- walking speed of the passenger (dependent on whether the passenger is a healthy adult, a child, or a passenger with a disability);
- class of the passenger (first class, economy class etc.); and
- the passenger's individual boarding time (determined when passenger is seated).

The rules governing the behaviour (or rather propagation) of the passengers in the plane takes into consideration the passengers' walking speed. We assumed that in the space of one seat-row, two consecutive passengers can stand in the aisle. Thus, the aisle of the plane (also modelled as a vector) was created such that it has two elements for every seat row it bypasses. According to the rules, a passenger could move ahead in the aisle only if the element in front is unoccupied.

Assumptions

- The aircraft has a single entrance. Most airports have facilities for only one boarding entrance to each plane.
- Not all passengers walk at the same speed. We created three categories of passengers who move through the plane at different speeds. The notion of speed is difficult to implement in cellular automata, due to the finite time-step nature of the algorithm. Thus, we used probabilities. Rules were constructed in such a way that a healthy adult definitely advances one matrix- (or rather aisle-) element per time step. Since children would move slightly slower, they only advance with a probability of 0.7. Lastly, disabled, frail or handicapped people would move the slowest, and were thus forced to advance with a probability of 0.3. In this way, an idea of speed is introduced, where slow passengers hold up the faster ones in the aisle. It is also assumed that passengers do not pass one another in the aisle.

- The distribution of the three categories of passengers is: 2% disabled, frail, or handicapped; 10% children; and the remaining 88% healthy adults. These assumptions are based on semi-educated guesses, since very few data on this matter are available.

- When a passenger gets to the row of the allocated seat, the passenger must stow hand luggage, blocking the aisle for 5 time steps.

- If a passenger reaches the row of the allocated seat, a similar time-penalty is introduced, depending on how many seated people the passenger has to pass over to reach the seat. This time allows for passengers to move out of their seats and into the aisle to permit the given passenger to pass. During this time, obstruction occurs in the aisle, leading to a time delay. This time delay was implemented using a quadratic method: A fixed time delay was multiplied by the square of the number of seated passengers in the way. We considered this to be a realistic model, since several people moving into the aisle would cause a larger time delay for other passengers trying to pass them.

- The time units quoted in the results section are arbitrary and represent individual steps of the cellular automaton. Nonetheless, the time delays are scaled so that their magnitude, in terms of movement of passengers in the aisle, is reasonable. The scale was calculated as follows:

  - A healthy adult passenger advances one element in the aisle vector during each time step if not obstructed. This would be approximately 0.5 m.
  - The average walking speed in an aircraft of a healthy adult is taken to be 0.75 m/s.
  - Thus, one algorithmic time-step would is roughly 0.67 s.

  Based on these assumptions, the delays were calculated as described above.

- Most planes have more space per person in first class and business class than in economy class. Thus, we implement large time delays for luggage stowing in economy class, smaller ones in business class, and the smallest in first class.

- We assume that passengers move in only one direction in the aisle during boarding, since they all have allocated seat numbers and can (we hope) read.

The model is later expanded to accommodate larger planes with two aisles, where similar assumptions are made.

Step-by-Step Explanation of the Algorithm

First, a seating-plan is loaded, in the form of a matrix, in which the elements represent the seats in the plane numbered sequentially. Our code was constructed such that a fixed, predetermined seating plan could be loaded (for specified aeroplane layouts) or that a seating plan with a chosen number of rows and seats per row could be used.

The passenger vector is then initialized. A load factor is chosen, which determines what fraction of available seats is occupied. This, of course, affects the length of the passenger vector. (Length of the passenger vector is equal to (load factor) $\times$ (total number of available seats)). Each element in this vector has a passenger number and corresponding values for this passenger's seat, speed, and class. This vector is rearranged in different ways for the various boarding strategies, by changing the sequence of the passengers before they enter the plane, so that, for instance, passengers with window seats board first.

Next, a vector representing the aisle is created. This vector has two elements per seat-row. Each vector element can contain a single passenger. As passengers move into the aisle, their passenger numbers are stored in this vector.

The propagation / motion of passengers through the aisle is implemented in finite time-steps. The aisle is checked element-by-element from the rear of the plane. When a passenger is encountered in an element, a check is carried out whether another passenger is present in the aisle element directly ahead. If that element is unoccupied, the passenger moves into this aisle-element with the probability (speed) associated with that individual. This check continues through the entire aisle until the entrance of the plane is reached. If the element of the aisle at the entrance to the plane is unoccupied, another passenger is extracted from the passenger vector and fed into the aisle vector. Then another time-step iteration is initiated. The process can be summarised as a sequential checking of the entire aisle (and propagation of passengers through it) during each time-step, and the feeding of new passengers from the passenger vector into the aisle vector.

After any passenger advances one element in the aisle, a check is carried out for whether the passenger reached the row of the assigned seat. If so, the row containing the seat is checked for seated passengers obstructing the path, and the described time delays are implemented. A delay for the loading of each passenger's hand luggage is also initiated when the passenger reaches the row of the allocated seat. Qualitatively, these delays are instituted in such a way that they result in this passenger spending a number of time steps stationary in the aisle.

When time delays expire, the passenger is "seated" and is removed from the aisle.

The entire algorithm is iterated until all passengers are in their allocated seats and the aisle is empty. The time taken for this entire process is recorded and stored.

For a given initial setup of the passenger vector, the entire simulation was run over several iterations to obtain statistically relevant values for:

- Average time taken for the entire boarding process. This is an indication of how effective the boarding process is, since it is in the interest of the airlines to minimize the total boarding time.
- Standard deviation for this average total boarding time over all iterations. The absolute standard deviation is a quantitative measure of the consistency of the boarding procedure, i.e., how sensitive the strategy is to randomness. The relative standard deviation (absolute standard deviation divided by average total boarding time) is a qualitative measure of the consistency of the boarding times and allows comparison between the various strategies and aircraft types.
- Average time (and standard deviation time) that it takes each passenger from when entry until being seated. The standard deviations show how uniform / consistent the boarding time per passenger is.

For larger planes and for custom layouts of the seating plan, we implemented an option for a second aisle vector. The algorithm is carried out as above, with the sequential checking procedure simply being carried out in both aisles during each time-step. Yet some modifications are required: Still only one line of passengers enters the plane; this line has to split into the two aisles. This is done by checking whether the passenger at the entrance to the plane sits on the left half or the right half of the plane, and feeding the passenger into the relevant aisle vector. If the seating layout of the plane has an odd number of seats per row, passengers sitting on the middle seats enter the aisle that first has an unoccupied first element. If the first elements of both aisles are open, the passenger enters either aisle with a 50% probability. The rest of the algorithm progresses as for the single-aisle case.

Description, Implementation and Results

We describe the various boarding strategies, and the qualitative results for each, in detail. **Table 1** gives numerical results.

The load factors used in the simulations are based on statistics obtained from Transport Canada [2004]. In-depth analysis of the results follows the descriptions.

1. **Random boarding**
   Description and algorithmic implementation
   Here the seat numbers in the passenger vector are arranged at random, so that the sequence of passengers entering the aisle at the front of the aircraft is random. Random boarding is common and will thus be used as a reference for comparison with other methods.

Table 1. Results for various aircraft and boarding methods (originally in an Appendix).

Table 1 - Results for various aircraft and boarding methods

	Method:	1	2	3	4	5	6	7	8	9	10
Fokker 50 (54 seats)	Ave total boarding time	207.4	166.5	290	196.7	151.2	269.7	155.6	197.2	149.1	157.9
	Abs. std dev total boarding time	28.7	33.5	32.4	25.5	26.1	31.8	23.4	28.3	24.2	24.4
	Rel. std dev total boarding time	0.138	0.201	0.112	0.13	0.173	0.118	0.15	0.144	0.163	0.154
	Ave individual boarding time	110.1	102.7	152.5	106.7	94.5	143.8	89.8	106.7	92.3	92.1
	Abs. std individual boarding time	51.6	32.6	83.0	48.2	29.4	78.2	37.9	48.5	29	38.3
	Rel. std individual boarding time	0.469	0.317	0.546	0.452	0.311	0.544	0.421	0.454	0.314	0.416
Boeing 737-400 (153 seats)	Ave total boarding time	485.5	431.8	671.6	454	404	616.6	377	442.5	392.9	372.1
	Abs. std dev total boarding time	51.9	63.1	59.2	46.6	54.2	50.1	53.1	39.9	50.5	41.6
	Rel. std dev total boarding time	0.107	0.146	0.088	0.103	0.134	0.081	0.141	0.09	0.129	0.112
	Ave individual boarding time	244.2	251.4	336	233.6	236.6	313.4	219.3	232.8	233.3	207.8
	Abs. std individual boarding time	119.3	90.6	193.5	111.7	82.9	177.5	97.2	109.2	81	94.9
	Rel. std individual boarding time	0.489	0.36	0.576	0.478	0.351	0.566	0.443	0.469	0.347	0.456
Boeing 777-200 (340 seats)	Ave total boarding time	828.4	741	1058.2	801.7	697.4	1000.6	684	767.4	691.1	699.1
	Abs. std dev total boarding time	60.5	70.5	64.1	62.5	63.8	61	59.5	66.1	59.3	74.1
	Rel. std dev total boarding time	0.073	0.095	0.061	0.078	0.091	0.061	0.087	0.086	0.086	0.106
	Ave individual boarding time	412.2	430.6	509.7	397.7	413.6	479.3	404.1	401.6	421.2	392.8
	Abs. std individual boarding time	191.8	144.3	292.4	184.1	135.6	275.5	150	174.4	135.4	158.6
	Rel. std individual boarding time	0.465	0.335	0.574	0.463	0.328	0.575	0.371	0.434	0.321	0.404
Custom Large Plane (792 seats)	Ave total boarding time	1956	1837.6		1902.3	1803.8	2189.8	1732	1752.3	1730.9	1661.3
	Abs. std dev total boarding time	113.7	114		105	113	107.5	115.4	115	105.5	121.5
	Rel. std dev total boarding time	0.058	0.062		0.055	0.063	0.045	0.067	0.066	0.061	0.073
	Ave individual boarding time	948.5	964.4		902.2	945.1	1124	896.5	937.2	974.5	929.6
	Abs. std individual boarding time	483	403.1		477.4	394.6	549.8	417.3	425.7	399.5	406.3
	Rel. std individual boarding time	0.509	0.418		0.529	0.418	0.578	0.465	0.454	0.410	0.437

worst performance

best performance

Results
Random boarding yielded results which were, in general, only faster than those methods that board the plane from front to back. This method never obtained the worst results in any of the measured categories.

2. **Dividing passengers into three groups and beginning boarding with the rear group**
   Description and algorithmic implementation
   First the passenger vector is arranged randomly. By finding the highest available seat number, the seating plan is divided into three equal groups. The seat numbers in the passenger vector are arranged in these three groups. The group at the back of the plane boards first, the middle group second, and the front group boards last. Thus, the three groups are internally still arranged at random.
   Results
   For all aircraft sizes, this method yielded faster total average boarding times than random boarding. For larger aircraft, the average boarding time per passenger was larger than for random boarding. This may be explained due to each individual's initial seating time. For random boarding, very soon after boarding commences rapid front-positioned seating occurs as people seat themselves randomly; but for this method, people start seating themselves only after the rear passengers move to the back of the plane. Thus, the aisle has to be traversed before any seating occurs. This effect is greatly pronounced if the plane is large and the aisle is longer. The relative deviation of passenger boarding times was lower than that of the random method, which implies that these individual times are more uniformly distributed.

3. **Dividing passengers into three groups and beginning boarding with the front group**
   Description and algorithmic implementation
   As before, the available seats are divided into three equal groups. The passenger vector is arranged in such a way that boarding commences with the front group. The middle group boards second and the rear group last. As before, the three groups are internally still arranged at random.
   Results
   This method performs worst in almost all aspects. However, the relative standard deviations of the total boarding time are among the best. The poor performance of this particular method can be explained by the congestion of passengers near the entrance to the plane, since the front-seated passengers board first and obstruct flow through the aisle(s). This method was not tested on the largest aircraft, since it was evident that it was the most ineffective boarding strategy.

4. **Beginning boarding by filling window seats first**
   Description and algorithmic implementation
   First, the passenger vector is arranged randomly. By checking which seat

numbers are in the first and last column of the seating matrix, passengers with window seats (arranged randomly) are extracted from the passenger vector, which is then rearranged in such a way that these passengers board first. The rest of the passengers are queued behind them at random.
Results
This method is faster than random seating but is out-performed by seating in groups from the back of the craft to the front. The standard deviation in total boarding time is small for all aircraft and is the best in this category for the largest aircraft.

5. **Beginning boarding by filling window seats first, and dividing passengers into three groups and beginning boarding with the rear group**
   Description and algorithmic implementation
   As above, the window seats are extracted and placed at the front of the passenger vector. Then the passenger vector is then divided into three groups (front, middle and back), and boarding commences with the group at the back of the craft.
   Results
   This method is a good improvement on merely commencing boarding with window seats. Thus far, it yields the best results for average total boarding time; but the average time per passenger is not the best.

6. **Beginning boarding by filling window seats first, and dividing passengers into three groups and beginning boarding with the front group**
   Description and algorithmic implementation
   As above, passengers with window seats are placed at the front of the passenger vector. Then the passenger vector is then divided into three groups (front, middle and back), and boarding commences with the group at the front of the craft.
   Results
   Especially with large aircraft, this method performed poorly. As with method 3, this can be attributed to the congestion at the entrance of the plane.

7. **Dividing passengers into three groups, beginning with the back group, and extracting window seats**
   Description and algorithmic implementation
   Again the passengers are grouped into front, middle and back, with the back group at the beginning of the passenger vector. The window seats are then extracted and placed at the front of the vector. Boarding begins with window seats (arranged back to front) and then with normal seats (grouped back to front).
   Results
   This method is the best of the methods mentioned thus far, with overall good performance in all aspects.

8. **Filling seats inwards towards the aisle(s)**
   Description and algorithmic implementation

For planes with a single aisle: Each passenger's seat is located in the seating plan matrix, and its distance (in terms of seats) from a window seat is calculated. The passenger vector is then rearranged in such a way that the passengers are arranged in terms of this distance from the window seats, beginning with the smallest distance (i.e., with the window seats themselves). The plane fills up from the window seats towards the middle of the plane (which is the aisle).

For planes with two aisles: Essentially the plane is divided into two halves, each aisle being the centre of one half. For simplicity, planes with even numbers of seats between the two aisles were considered, to simplify the location of the middle of the plane. Each half of the plane is then treated as in the previous boarding strategy (that is, as if it were an individual plane with one aisle), and the passenger vector is arranged such that seating begins with passengers furthest from the aisles, and ends with passengers closest to the aisles.

Results
This method is an improvement on the strategy of boarding window seats first (method 4). For all aircraft except the smallest (Fokker 50), the average total boarding time is shorter than for method 4. However it is not among the best methods in any particular aspect, though both the average boarding time and the total boarding time are fairly stable (that is, they have relatively small standard deviations).

9. **The passengers are first sorted in groups from back to front, and these groups are further sorted towards the aisle(s)**
Description and algorithmic implementation
As in strategy 8, the seats are arranged to fill towards the aisle(s). The seats are then further sorted into three groups, and boarding commences with the back group. The table in the left of **Figure 1** shows the way in which the passenger vector is sorted before boarding for a simple aircraft layout with one aisle. The numbers in the figure show in which order seats from the various sections are sorted in the passenger vector.
Results
This method performs best in most points (as is clear from inspection of **Table 1**). For small aircraft, it is the fastest method. Throughout, the standard deviation of passenger boarding times is good, as is the absolute standard deviation of total boarding time.

10. **The passengers are first sorted towards the aisle(s) and then further divided into groups from back to front**
Description and algorithmic implementation
Again the three groups are created, from the back of the craft to the front. Then the passengers are sorted within the groups such that the seats farthest from the aisles board first and those closest to the aisle board last. The right-hand table in **Figure 1** shows how the passenger vector is sorted for a

simple aircraft layout with one aisle; low numbers seat first.
Results
For total boarding time of the largest aircraft, this method yields the best result. For other aircraft, it also performs well in this regard. However this strategy is not very consistent, since the standard deviations of the total boarding times are among the highest, especially for large aircraft. For all aircraft sizes, this method yields shorter average boarding time per passenger than method 9.

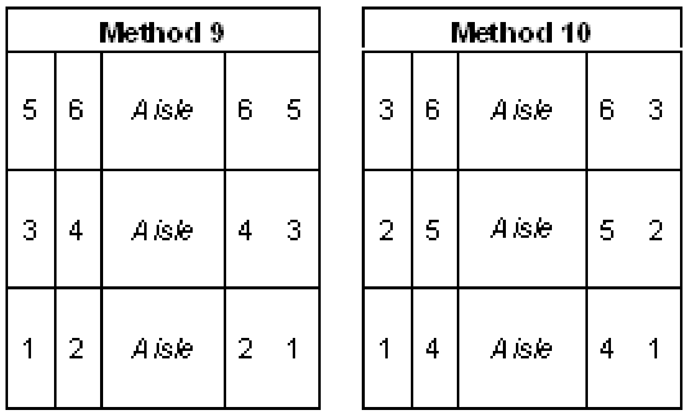

Figure 1. Illustration of seating strategies 9 and 10 (low numbers seat first).

Short Summary of Results

For small aircraft (roughly 50 seats), methods 9, 5, and 7 yield the best average total boarding times.

For slightly larger aircraft (roughly 150 seats), methods 10, 7, and 9 yield the best average total boarding times.

For medium aircraft (roughly 300 seats), methods 7, 9, and 5 yield the best average total boarding times.

For large aircraft (roughly 800 seats), methods 10, 9, and 7 yield the best average total boarding times.

It is thus clear that

methods 5, 7, 9 and 10 are the most efficient strategies.

They have in common that they begin boarding with passengers seated in the rear of the plane. Furthermore, they implement a further sorting criterion (for instance, boarding window seats first or filling the columns of the plane towards the aisles).

Random boarding was among the three most *in*efficient methods for all plane classes.

Sensitivity Analysis

To see how sensitive the algorithm is to variations in its parameters, we carried out additional simulations.

- **Changing the percentage of disabled / frail / handicapped passengers**

  We carried out several simulations with varying percentages of disabled or handicapped passengers. Some methods were affected more strongly by these changes than others.

  As an example, we provide results from a simulation with a Boeing 777-200 (midsize aircraft), with the same load factor as used previously (0.78). We change from 2% of the total passengers assumed to be handicapped to 6%.

  The percentage increases in average total boarding time for methods 1, 9, and 10 were 16%, 13%, and 19%. The percentage change does not vary too greatly for the various methods.

- **Investigating the effect of various load factors on the total boarding time** From the results obtained, we chose one method (method 9) and ran the simulation over a range of load factors. We found a strong linear relation between load factor and average total boarding time. We conclude that it is fairly irrelevant what load factor is used to compare boarding procedures, provided the same load factor is used for all.

Advantages of Our Model

The model can be customised to accommodate any seat plan specification (an aircraft with either one or two aisles). Two decks on a plane could simply be modelled as two separate aircraft with their individual seating configurations.

Our measurements are sensible in that they provide information from 200 iterations of each boarding procedure. Thus, the accuracy of the specific boarding measurements is reliable.

We strove to keep all parameters fixed during the simulation of each boarding strategy. This ensures that if a parameter has been allocated an unrealistic value, then this fault has a reduced effect on the outcome of the experiment and, more specifically, on the comparison of boarding strategies.

Many different boarding strategies were implemented. Some were combined with others to yield a more substantial result. In essence, any of the boarding strategies can be combined in the model to produce many more procedures. We did, however, select strategies that we assume to be realistic and that yield a spread of data and results that are informative.

Improvements, Comments

- We do not address deboarding strategies. We are convinced, though, that it is significantly more challenging to set up effective boarding strategies, since this involves arranging passengers before they board the plane. In a sense, deboarding is inherently a more structured process. We also believe that a simple reversal of the more effective boarding procedures should save time during deboarding.

- The speeds of passengers are strongly discrete in the model. Distinctions are made only among frail/handicapped passengers, children, and healthy adults. It would have been more realistic to implement a probability distribution of walking speeds.

- Throughout the model, the assumption is made that passengers move in only one direction in the aisle. This does not accommodate the fact that sometimes people move opposite to the stream of passengers in the aisle.

- In our model, passengers cannot pass in the aisle. This is not realistic, though in most cases passengers would probably wait for a person ahead of them to stow luggage before passing. This could slow boarding and would affect the outcomes of some boarding strategies (for instance, boarding from the front would have yielded a significantly shorter boarding time). Nonetheless, we believe that our model is inherently systematic and that the obtained results are meaningful and believable.

- It would be sensible to allow for two doors into the plane. However, one door at the front of the plane and one at the rear could be likened to boarding two separate planes, each from one entrance.

- We could have investigated how division into more groups would have affected the simulations. Nonetheless, we believe that it is not reasonable for airport staff to have to divide passengers into so many groups, as this process itself would be time-consuming.

- Special seat allocations and boarding strategies for disabled people could have been considered, but this would not have affected the final outcome of the simulations greatly, due to the small percentage of disabled passengers. Perhaps one strategy should have involved seating all disabled passengers in the front of the plane so that they do not obstruct motion through the aisles and that they do not have to walk as far in the plane.

- Many of our boarding strategies do not allow for passengers to board in groups (for instance, mothers with their children), and this could cause inconveniences in its implementation in the real world.

- The various delays in the boarding algorithm were based on guesses that we made by comparing the average walking speed of a healthy person to the average time that we assumed would be needed to stow hand luggage. These delays were then implemented in the finite time-step nature of the algorithm, and could have been researched more accurately.

Conclusion

The task assigned to us was to devise and test various strategies for boarding procedures for various classes of aircraft. Using the approach of an algorithm based on a finite time-step cellular automaton, we obtained some clear results.

From our simulations, we find that certain boarding procedures result in significant savings of time. The most efficient strategies all apply two filters to the passengers before the plane is boarded. One filter involves sorting passengers so that that those farthest from the entrance board first, and the other sorts passengers according to seat columns. Nonetheless, methods that disrupt boarding of groups of adjacently seated passengers may be logistically difficult to implement or even irritate passengers (e.g., method 10).

The most outstanding of these are implemented as follows (see **Figure 2**):

Method A: The aircraft is divided in groups seated from the rear to front, and each of these groups is further sorted from window (and centre) seating towards the aisle(s).

Method B: The passengers are first sorted from window seats (and centre seats) towards the aisle(s). They are then further divided into groups from rear to front. (The figure illustrates how this would be implemented in a two-aisle aircraft)

Time differences in total average boarding time between the most efficient and least efficient strategies are up to 3 min for small planes and 5–6 min for larger planes.

Essentially, an optimised seating strategy merely divides the plane into sections and dictates which sections are boarded first. Thus, once a strategy is selected, it would be easy to include these sections on the tickets of passengers, and to have the passengers group themselves as desired (for instance, by allotting areas at the boarding gates to the various passenger groups, or calling them separately for boarding). In this way, the organisation of the passengers into the desired sequence need not imply a significant time delay at all. The trade-off between shortened boarding time and required organisation time is especially pronounced with small aircraft.

Methods with the best total boarding times do not necessarily guarantee the shortest average boarding time per individual passenger. This is important to note, since the implementation of such a strategy may infringe on convenience to the passengers. The average boarding time per individual passenger for some methods was greater than that for random boarding, especially

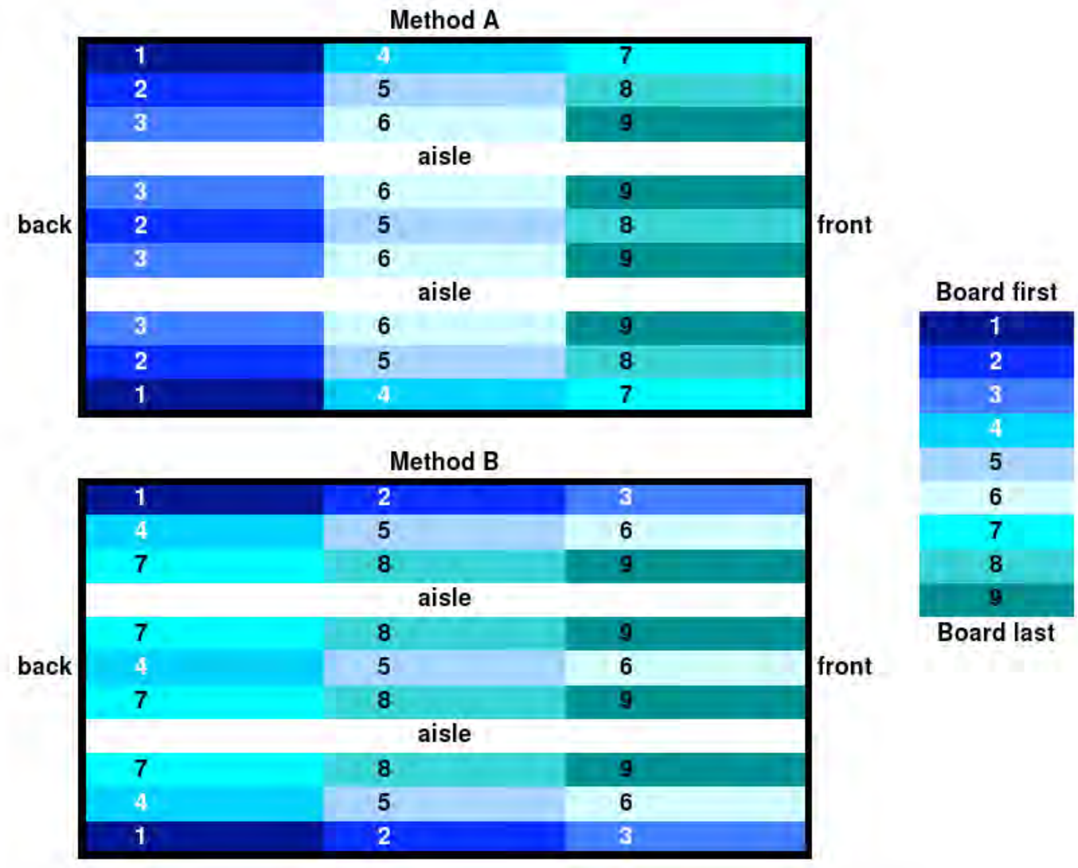

Figure 2. Implementation of Methods A and B in a two-aisle aircraft.

for large aircraft. This is not necessarily relevant, since random boarding has a larger spread in individual boarding times. Furthermore, the differences in average boarding time per passenger in relation to the total boarding times of these methods were relatively small. Yet a rigorous sorting of passengers prior to boarding may very well be perceived as irritating by many passengers. This effect should be minimised by performing the sorting efficiently and in a simple manner (as suggested above).

It is easier to group people by seat row of the aircraft than by column, since passengers often travel in groups and some sorting methods would disrupt these groups. Thus Method A would most probably be more practical to enforce than Method B. The event of passengers not abiding to the desired procedure could cause disruption of the boarding process.

In conclusion, *we recommend Method A*.

Airports and airlines could further shorten boarding times by making infrastructure changes, such as allowing passengers to board from both ends of the plane.

We do not believe that implementation of these structured boarding strategies in the real world would result in an administrative waste of time that outweighs the potential boarding time savings.

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Top, from left: Advisor J.H. Van Vuuren, Chris Rohwer; bottom: Andreas Hafver, Louise Viljoen.